

INSTITUTO TECNOLÓGICO Y DE ESTUDIOS  
SUPERIORES DE MONTERREY  
CAMPUS MONTERREY

Graduate Program in Electronics, Computing,  
Information, and Communication



Qualitative Knowledge Acquisition Using  
Fuzzy Logic and System Dynamics

Dissertation

Presented as a partial requirement to obtain  
the academic degree of  
Doctor of Philosophy  
in Artificial Intelligence

by

Rafael Ernesto Bourguet Díaz

Monterrey, N. L., May 2003

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# QUALITATIVE KNOWLEDGE ACQUISITION USING FUZZY LOGIC AND SYSTEM DYNAMICS

Rafael Ernesto Bourguet Díaz

ITESM Campus Monterrey, May 2003.

## **Abstract**

Business models based on knowledge have increased the demand for tools to acquire and represent this intangible asset of organizations in computer-based systems. Qualitative knowledge is the knowledge contained in mental models, in the “back of our heads”. The problem is how to acquire it when many of the times the owner is not even aware of it. The issue becomes challenging when the knowledge is about dynamics of complex systems, that is, how our social, financial, technological and ecological systems evolve through time.

This research proposes a method to carry out qualitative knowledge acquisition of dynamics of continuous complex systems using Fuzzy Logic and System Dynamics. The method holds a different approach over existing methods by (1) joining both techniques and (2) using Fuzzy Logic as mapping function that transforms information into action, instead of a function for managing parameter value uncertainty. The focus is toward the modeling of mental models of decision-makers and policy makers in a context of business administration. The technical issue is the knowledge acquisition when scarce or non-numerical data are available and only individual or collective mental models are the information sources. The method proposes the construction of a model comprised by two subsystems: a virtual decision-maker and a business process.

The method is applied in a context of a hotel administration with the participation of a collaborative team of three persons. Simulation results are analyzed and discussed under principles of feedback dynamic systems to validate the method.





# Dedication

To my parents:

Enriqueta and Roberto.

To my sisters and brothers:

Roberto, María de Lourdes, Enriqueta, José Romárico, and Monique.



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# Chapter 1

## Introduction

*“The positive side is that if a human can solve a problem or engage in some intelligent activity, then machines can ultimately be constructed to perform in the same way.”*- Positive side of the Church-Turing thesis and central thesis of the AI movement.

(Kurzweil, 1992, 117.)

*Can machines make decisions  
on complex systems (social systems)?*

### 1.1 The Problem: Qualitative Knowledge Acquisition

Qualitative knowledge is the softest part in human organizations and the hardest part to manage. It is the knowledge gathered by experience which most of the times is not registered in papers, or databases or other storage media. It is just contained in our mental models, in the “back of our heads” (Ljung and Glad, 1994, 15.)

The problem is how to acquire this knowledge that in many of the times the owner is not even aware of it. The issue becomes more challenging when the knowledge is about dynamics of complex systems, that is, how our social, financial, technological and ecological systems evolve through time (Bourguet and Soto, 2000, 303.) Soft laws seem to regulate their behavior according our perceptions.



## 1.1.1 Problem Formulation

### 1.1.1.1 Objective

The objective of this research is to develop a method-based on Fuzzy Logic and System Dynamics that support the process of Qualitative Knowledge Acquisition about dynamics of continuous complex systems.

### 1.1.1.2 Focus

The focus is toward the modeling and simulation of policymakers' mental models on socio-technical-economic systems.

The technical issue is the process of the Knowledge Acquisition of dynamic complex systems when scarce or non-numerical data are available and just individual or collective mental models are the information sources.

### 1.1.1.3 Research Questions

Two research questions are formulated:

1. Based on Fuzzy Logic and System Dynamics, how to elicit uncertain, incomplete, and qualitative knowledge of the dynamics of complex systems and getting it into a model for computer-based simulation?
2. When is adequate to use Fuzzy Logic into System Dynamics to represent dynamic complexity?

### 1.1.1.4 Research Justification

**Theoretical Value:** As so far to the author's knowledge, there is only one published work by (Tessem and Davidsen, 1994) in the literature that explore the use and benefits of working simultaneously Fuzzy Logic and System Dynamics (Bourguet and Soto, 2002.) The difference between this research and the previous one is the use of Fuzzy Logic to represent policies or rules to make decisions instead of the use of fuzzy numbers as alternative to probabilistic methods for handling uncertainty and vagueness in parameter values. The article of 1994 is perceived by this research as a valuable piece of knowledge but with an undesired collateral effect in the community of System Dynamics: a lost of interest for using Fuzzy Logic in the construction of simulation models.

**Convenience:** The research pretends to clarify when Fuzzy Logic is adequate to use in System Dynamics models during a process of knowledge acquisition. A prime convenience is to transfer some of the benefits that Fuzzy Logic has brought to the area of control systems by representing qualitative knowledge of human operators in physical systems to the discipline of System Dynamics by representing policies of decision-makers in business and administration systems.

**Methodology value:** This research proposes an original method by integrating methods of three main disciplines of knowledge: Feedback Systems (from Control Engineering), Fuzzy Logic (from Artificial Intelligence) and System Dynamics (from Business and Administration).

### 1.1.2 Motivation and Background

The motivation of this effort is the search of a method to help organizations to elicit and represent their qualitative knowledge by using intelligent systems. Sources of knowledge are the mental models of decision-makers and policymakers. The method should address the knowledge acquisition "bottleneck" problem described in Section 2.1.2.

Once this knowledge is explicitly available, the organizations may decide to use it to accelerate their learning processes on complex environments. For instance, by practicing decision making in simulated scenarios with high degree of uncertainty and risk.

Decision-makers and policymakers are responsible of maintaining under sustainable control behaviors of industrial, rural, and urban systems in an uncertain environment. This environment is changing amazingly fast and becoming more complex at every moment. They have to learn many times by experience (trial and error) with persons, money and ecological consequences. Being intelligent they recognize and fear the consequences. The result is they learn a lot less and slower than they would under other circumstances (Morecroft and Sterman. 1994). Lessons from engineers with simulators of nuclear power plants, chemical plants, airplanes have showed the power of the simulators for learning and designing purposes. The process of learning is accelerated when the fear of making mistakes in these artificial environments is eliminated.

### 1.1.3 Knowledge Acquisition

The processes of knowledge acquisition, knowledge representation and the method of inferring decision rules are the fundamental issues in the design and development of intelligent systems. By its own side, knowledge acquisition has proved to be one of the greatest challenges in these developments. It involves a “knowledge engineer” interviewing the appropriate human experts and literally writing down with a computer language all of the relevant knowledge and decision-making rules used by the human expert (Kurzweil, 1992, 211.)

Knowledge acquisition is mainly identified as a phase in the process to build knowledge-based systems in Artificial Intelligence (AI). However, it is also found in the processes of constructing knowledge-based control systems and simulation model of qualitative knowledge in System Dynamics.

The process of knowledge acquisition involves two activities: (1) identifying and eliciting relevant technical knowledge, and (2) registering and getting it into computable form so it can be used to solve a problem (Gonzalez and Dankel, 1993, 348.)

Under this context, the interest of this research belongs to efforts of knowledge acquisition where:

- Internal models for simulation are required.
- There is no data, cases or training patterns available for machine learning methods.
- The domain experts are decision-makers from business and administration.

One of the problems is to collect the enough volume of information and rules involved, but another and bigger one, as (Kurzweil, 1992, 211) states, is “that while humans experts are capable of solving problems within their domains of expertise, they generally do not know how they accomplish these tasks. The skill required of the knowledge engineer is to be able to extract the decision-making process from the domain experts despite their not being aware of man elements of this process.”

One of the challenges in the process is finding a source of expertise or knowledge. The best and most experienced domain persons are generally running out of time and do not have much time for participating as necessary for the construction of the system. Additionally, in complex systems where many perspectives of the same situation are involved, multiple experts equally skilled in the same field disagree on how to do the job.

### 1.1.4 The Domain

The domain is the computer-based simulation of decision-making process in management. Management is the process of allocating people, money and technology to attain business goals in an organization through the conversion of information into action.

The conversion of information into action is called decision-making (Forrester, 1994).

#### 1.1.4.1 Decision-making process

Three parts form the decision making process (Forrester, 1994, 51): (1) formulation of a set of desired conditions, (2) observation of the current perceived conditions, and (3) generation of corrective actions to reduce gaps among desired and perceived conditions. This third part, generation of corrective actions is formed as well by three phases in the process (Simon, 1960): (1) intelligence, (2) design, and (3) selection. They respectively refer to the activities of diagnostic, generation of alternatives, and selection of the alternative to be implemented. The three phases can be systematically applied, following seven steps used in the Case Teaching Method (Mauffette-Leenders, Erskine, and Leenders, 2001, 34). They are: (1) define the issue, (2) analyze the case data, (3) generate alternatives, (4) select decision criteria, (5) analyze and evaluate alternatives, (6) select preferred alternative, and (7) develop an action and implementation plan.

Since managers are who convert information into action -make decisions- then successful management depends on the effective selection of information and execution of the conversion. In computer-based simulation, managers are modeled as information converters that transform flow of information into stream of decisions that control actions within an organization (Simon 1976, cited in Forrester 1994).

Feedback loops are the structures that control change in every system. Information, decision-making, and action are structured in a feedback loop: information is the input to a decision-making point that control actions, which will yield new information that in turn feedback the decision-making point. Business behaviors such growth, decline, goal-seeking, and oscillation take place within the control of feedback loops.

The process of decision making is based on explicit and implicit policies though which information is interpreted.

#### 1.1.4.2 Policies

Policies are rules that govern decisions (Ackoff, 1992). They are statements that define the relationship between information inputs and resulting decisions. In the literature of management, they are referred to as decision rules (Forrester, 1994, 58). In the literature of AI, specifically on knowledge-based rule systems, they are called knowledge-rule. In the literature of control engineering, specifically dealing with linear systems, they are called “transfer functions” (Forrester, 1994, 58).

In business and industrial organizations, formal policies can be found in written form for guidance of the subordinates. However, most of the day-by-day operating policies are informal and have high influence in the behavior of the organization. “Informal policies results from habits, conformity, social pressures, ingrained concepts of goal, awareness of power centers within the organization, and personal interest” (Forrester, 1994, 58).

#### 1.1.4.3 Decisions

Decisions are actions taken at any particular time as result of applying policy rules to a particular perceived condition that is present at the moment. Decisions are based on the states of the system and control the flow of people, money and technology. These flows in turn modify the states of the system.

## 1.2 The Approach

### 1.2.1 Hypothesis

The tentative answers to be validated for the two research questions formulated in Subsection 1.1.1.3 are presented as follows.

#### **Tentative answer to research question 1.**

The method to acquire qualitative knowledge of dynamic complex systems using Fuzzy Logic and System Dynamics is based on three levels for knowledge acquisition, which are described in detail in Chapter 3 and are listed below.

For knowledge elicitation:

- High level mappings - mental models, verbal models and causal diagrams.

For knowledge registration and codification in computer-based simulation model:

- Intermediate level mappings - flow-level diagrams, graphical and symbolic language.
- Low level mappings - numerical equations and fuzzy rules.

### **Tentative answer to research question 2.**

Fuzzy Logic is adequate to use into System Dynamics during a knowledge acquisition process when:

- the policies that govern decisions are the central issues in the modeling process, and
- the attention is explicitly paid on the rules that transforms information into action in the learning process.

In this context, policies have to be understood as rules that govern decisions. Policy representation consists of three steps:

- elicitation of policies from the decision-makers,
- codification of the policies in a computer, and
- use of the policies in computational models to respond and generate new questions.

### **1.2.2 Goals and Non-Goals**

The goal of this research has been to develop understanding and a method on how to elicit and get mental models of manager and decision-makers into a computer-based representation. The research has been framed in the area of knowledge acquisition. It has taken Fuzzy Logic and System Dynamics as techniques to implement the method.

The technical goal has been to explore the use of Fuzzy Logic into System Dynamics. The intention is to integrate some of the benefits that Fuzzy Logic has brought to the area of Control Systems by representing qualitative knowledge of human operators to the discipline of System Dynamics by representing policies of decision-makers.

The non-goals are now established from the outset. This research has not attempted to handle Knowledge Representation process or generate causal explanations of problems or action taken by the machine. Neither has it addressed the problem of incorporating simulation models into

intelligent systems such as Model-Base Reasoning or Knowledge Based Simulation. This research has not either attempted to developed techniques for fuzzy controllers, learning or adaptive algorithms. Neither has it attempted to provide a computer-based business simulator as a research result. Finally, this research has not addressed the important issue of automated knowledge acquisition. Certainly, they are all-important areas of research and some natural extensions to this work may help advance the engineering practice in these advanced techniques.

### **1.2.3 Modeling as Knowledge Acquisition**

Modeling as Knowledge Acquisition assumes that models should capture the knowledge and mental data of policymaker. It should blend qualitative mapping with friendly algebra and simulation. Simulations are very important part of the process. They provide consistent stories about the future, but not predictions, which has been the traditional use in science (Morecroft and Sterman, 1994, xvii).

The modelers act as facilitators who designs and leads group processes to capture team knowledge (Morecroft and Sterman, 1994, xviii.) The facilitator can be considered as a knowledge engineer in this process.

In a context of Modeling for Learning Organizations, which is considered also in this research, the modelers design and deliver learning laboratories, which embed models in an overall learning context of group experimentation and dialogue. The purpose of the models is to support team reasoning and learning. Models have to encourage system thinking and scenarios planning (Morecroft and Sterman, 1994, xviii.)

### **1.2.4 Fuzzy Logic and System Dynamics as Knowledge Acquisition Tools**

Fuzzy logic and System Dynamics are used as tools to elicit and represent knowledge about management in this research.

"... fuzzy logic has emerged as a paradigm for approximating a functional mapping. ... one important issue- cost. A better question to ask is "What is the difference between the cost of a fuzzy logic approach and the cost of an approach based on X to accomplish a certain task?" (Yen, 1999, 153.)

Fuzzy Logic, although controversial since its beginnings, has proved to be an effective approach to deal with the trade-off between precision and cost in developing an approximate model of a complex system or function. Artificial Intelligence and Fuzzy Logic share a common objective: "to develop computational methods that can perform reasoning and problem solving

tasks that require human intelligence” (Yen, 1999.) Since 1990, Fuzzy Logic has emerged as a paradigm to approximate functional mapping and not only as an approach to manage uncertainty. Control Engineering has been the most successful area for industrial applications using Fuzzy Logic.

“System Dynamics is a method to enhance learning in complex systems. ... is grounded in the theory of nonlinear dynamics and feedback control... Because we apply these tools to the behavior of human as well as physical and technical systems, system dynamics draws on cognitive and social psychology, economics, and other social sciences. Because we build system dynamics models to solve important real world problems, we must learn how to work effectively with groups of busy policy makers and how to catalyze sustained change in organizations.” (Sterman, 2000, 4-5.)

System Dynamics, even still controversial in our days, however has proved to be an effective approach to deal with policy analysis and design in management. System Dynamics is based on the principles of Control Engineering and computer-based simulation to create understanding and knowledge about structures of complex systems. System Dynamics takes advantages of the following four facts. First, there is enough information of complex systems in the mind of the decision-makers to build a useful model. Second, any verbal model that expresses clearly an idea can be translated to a formal model in a computer. Third, the computer by its own nature can determine future dynamic consequences better than human on highly coupled, multiple-feedback-loops and nonlinear natures of real complex systems. Fourth, behaviors of dynamic systems can be represented, understood and designed using feedback principles (Forrester, 1995.)

System Dynamics was selected among other techniques related to qualitative knowledge because it is focused on enhancing human learning on complex systems, mainly dynamics of complex systems. Since the method uses engineering principles, it takes full advantages of the computational power of computers to create understanding and knowledge. These characteristics of learning and usage of computers are ideal for this research to elicit qualitative knowledge from humans and represent that knowledge in computer-based simulation models. Other techniques, such as Fuzzy Cognitive Maps (Kosko, 1986 cited by Dickerson and Kosko, 1993), (Kosko, 1992) and Qualitative Simulation (Kuipers, 1986) were found them limited in those characteristics. Fuzzy Cognitive Maps is an effective tool for data abstraction and synthesizing data into more useful formats (Perusich and McNeese, 1997, 7), (Perusich, 1996), (Hashimoto and Yamaguchi, 1997), (Lee, et al., 1998) but it is not interested on the dynamic behavior through time of complex systems. Qualitative Simulation is a technique that deals more with symbolic processing of qualitative data, exploration of new reasoning paths about physical systems, and



their causal explanation (Weld and DeKleer, 1990), (Fishwick, 1988), (Nissen, 1996), (Fouché and Kuipers, 1992), (Akiyoshi and Nishida, 1993) rather than eliciting and representing qualitative knowledge of complex systems where humans are involved.

Fuzzy Logic in Control Engineering and System Dynamics have at least one common objective: to develop understanding and knowledge on policy analysis and design in the search of improving dynamic behavior of systems.

This research represents an effort to integrate some of the benefits that Fuzzy Logic has brought to the area of Control Systems by representing qualitative knowledge of human operators in physical systems to the discipline of System Dynamics by representing policies of decision-makers in management of social systems.

### **1.2.5 Benefits**

A key benefit of this research is to have brought near Fuzzy Logic and System Dynamics to solve problems in complex systems. A hole of understanding and knowledge on how to use one in another is still present and demands for further research. This dissertation has pretended to fill a part of this hole with the proposed method. Control theory was used as a bridge to connect both approaches and as a tool to construct the method. From this bridge and point of view, Fuzzy Logic in control engineering and System Dynamics have a common goal: to improve dynamic behaviors of systems by analyzing and designing policies or control laws.

Specifically, the proposed method can be used to:

- carry out processes of qualitative knowledge acquisition on dynamics of complex systems
- represent management policies using Fuzzy Logic
- allow learning in designing policies via modeling

### **1.2.6 Procedures**

Analysis method has been the procedure to construct the proposed method for qualitative knowledge acquisition using Fuzzy Logic and System Dynamics. Analysis method allows generating knowledge, generating know-how (Ackoff, 1995, 31). Knowledge is contained in instructions. The fundament of analysis is based on the reductionism doctrine, which search of the indivisible element of the subject under study. In this research, the indivisible element to represent knowledge is the fuzzy if-then rule.

The three steps of the Analysis process are (Ackoff, 1995, 21):

1. Take apart the pieces of the object under study.
2. Analyze every piece.
3. Understand the object under study by integrating the understanding of every piece.

System Thinking has been used to perceive the reality during the modeling session with the participants. It is based on the method of Synthesis. Synthesis method allows generating understanding, generating explanations. Understanding is contained in explanations. The fundament of synthesis is based on expansionism doctrine, which search the functions of the system under study in another hierarchically higher system. In this research, the higher system is bounded in the concept of Modeling for Learning Organization, see Section 3.1.1 for development of this concept. The qualitative knowledge acquisition method is the system under study.

The three steps of the System Thinking Approach are (Ackoff, 1995, 30-31):

1. Identify the hierarchically higher system
2. Determine the function of the hierarchically higher system
3. Determine the function of the system under study into the hierarchically higher system

Scientific method has been used to construct and validate the obtained models.

### **1.3 Related Work**

The only work known so far by this research that explores the use of Fuzzy Logic into System Dynamics is “Fuzzy systems dynamics: an approach to vague and qualitative variables in simulation” by (Tessem and Davidsen, 1994). A formal paper, which suggest the use of Fuzzy Logic as an alternative to probabilistic methods for the management of uncertainty and vagueness in System Dynamics models. This focus implied the traditional way of using Fuzzy Logic, that is, for managing uncertainty. However, contrary to the author’s intention, this paper put farther away the interest on how to use Fuzzy Logic in the community of System Dynamics. The lack of formal interest remains until these days.

The authors emphasize the need for developing qualitative approaches to describe, analyze, and simulate complex dynamic systems. As their main motivation, they explicit the idea of applying successful techniques from fuzzy control to the management of social systems. In this context, the authors present an approach based on Fuzzy theory as alternative to probabilistic

distribution to represent and manage uncertainty. The implementation is specifically addressed toward the elements of a model by overloading variables and parameters, following (Fishwick, 1991, cited in Tessem and Davidsen, 1993). They limit their discussion to expressions characterized by fuzzy parameters, operators and functions, specifically to fuzzy numbers. They explicitly state they do not analyze Fuzzy relations. The examples developed are on basic deer population model, having *fertility* and *mortality* as fuzzy variables. The simulation results are not completely satisfactory because of behaviors are out of limits as the authors observe at the end. They remark then the need for better methods for simulation using Fuzzy logic.

An effect do not mentioned or maybe not perceived by the authors was the large number of parameters included by using two linguistic variables in their examples. The original model considered *fertility* and *mortality* as 2 scalar values to be estimated. In the first example, by applying the approach and defining *fertility* and *mortality* as linguistic variables with only one linguistic value each, and 4 parameters (trapezoidal membership function) for every linguistic value, the number of parameters to be estimated increases to 8. In the second example, the same linguistic variables but now with 14 linguistic values each, the number of parameter to be estimated increases to 56. So the simple comparison between 56 and 2 parameters that has to be found by trial and error, since it is supposed that there is no numerical values just mental models of the participants, makes a big difference in the complexity of the model. It makes sense then why Fuzzy Logic was not attractive for the community of System Dynamics anymore.

The approach of this dissertation addresses the relations and not the elements of the model. It can be seen as the complement of the research described above. Fuzzy Logic is then use as approximating functional mapping technique to represent the relations among information and action. This is a decision-making policy. In our opinion, this perspective is the same that Fuzzy Control has been using in its numerous and successful industrial applications (Hirota, 1995), (Lee, 1990), and (Yen, J., Lamgari, R., and Zadeh, L. A., 1995.) references cited by (Yen, 1999).

Contextual researches are found in (Adrian, 2000) who surveys what extent Fuzzy Logic has diffused throughout the Social Sciences, Business Medicine, and Philosophy. This investigation concludes that at least few researchers in each of the four academic disciplines have taken the challenge. Business, and specifically in the area of Operations, have published the greatest number of papers using Fuzzy Logic. (Rauma, 1996) expose the process of knowledge acquisition using Fuzzy models. The focus of the paper is toward the efforts at knowledge validation. The authors declare the current state of the art is perceived very poor with regard to knowledge verification and validation. Also they expose a comparison between the process of

knowledge engineering in expert systems and knowledge-based control systems. The main difference is in the knowledge base. An expert system has a description of events, but a control system has a description of actions. However, both systems have common processes to acquire the knowledge by interviews, questionnaires, among others. In (Haase, 2000), a combination of Balanced Scorecard and a decision support system based on Fuzzy Logic are combined into a methodology and a software tool. In this case Fuzzy rules are used to construct models of dynamic systems “if demand increase then unemployment decrease”, for example. In (Lim, 1999) a design for a knowledge acquisition tool is described but no examples are presented, only an architecture.

## **1.4 Guide to the Dissertation**

This dissertation is organized in five sections. Chapter 1 has introduced the problem of knowledge acquisition about dynamics of complex systems and briefly described the approach and its benefits. Chapter 2 describes the theoretical frameworks of Feedback Systems, Fuzzy Logic and System Dynamics. Chapter 3 presents our contributions to the Knowledge Acquisition Process about dynamics of continuous complex systems. Chapter 4 presents experimental results from an implementation of this approach, describing the computer-based simulation model of a hotel business administration. Chapter 5 presents the conclusions of this research and proposes ideas for future work.



## Chapter 2

# Knowledge Acquisition, Fuzzy Logic, and System Dynamics

*“The first principle of knowledge engineering is that the problem solving power exhibited by an intelligent agent's performance is primarily the consequence of its knowledge base, and only secondly a consequence of the inference method employed. Expert systems must be knowledge-rich even if they are methods-poor. This is an important result and one that has only recently become well understood in AI. For a long time AI has focused its attentions almost exclusively on the development of clever inference methods; almost any inference will do. The power resides in the knowledge.”*

(Edward Feigenbaum, Stanford University-  
cited by Luger and Stubblefield, 1993, 308.)

### 2.1 Knowledge Acquisition

Knowledge acquisition and incremental development form an interactive process of knowledge extraction in the development of a knowledge-based system. An incremental development involves the activities of selecting, eliciting, representing, validating, and integrating fragments of knowledge in a gradually and systemic way (Gonzalez and Dankel, 1993, 348.)

Even though this interactive process is mainly identified in the development of Expert Systems (ES), it is also found in the construction of simulation models when the object is to represent tacit knowledge (Bourguet and Soto, 2000, 304.)

### **2.1.1 Context and Definitions**

Knowledge acquisition is the process of eliciting knowledge from human beings and representing it into machines. It is considered the primary operation in implementing a knowledge-based system and the most arduous and longest of the development tasks (Gonzalez and Dankel, 1993).

Tacit knowledge refers to the capacity of effective response that is in the “back of our heads”, the knowledge that is not explicit. Everyone uses it at everyday activities: how to write with a pencil, how to drive a car, how to manage a business.

The essence of knowledge elicitation is carried out through series of interviews. On one hand, questions-and-answer interviews with domain experts when an Expert System (Gonzalez and Dankel, 1993, 349) is the case, and modeling sessions with decisions-makers when simulation models are the expected product.

The interview is the main effort of interaction with experts or decision-makers. Since, their time is usually a scarce and expensive resource, the interviews has to be optimized. Planning the interview and managing the process are two important elements.

Planning for each session consists of reviewing prior work, evaluating remaining issues to be done and setting objectives for the next interview. The overall success depends heavily on the planning done. However, planning becomes useless if the knowledge engineer does not adhere to the plan. Good practice is to inform the participants about the goal and remind it to them if the interview begins to loss focus.

These interviews are commonly developed in a format of one-on-one between expert and knowledge engineer, for expert systems (Gonzalez and Dankel, 1993, 348-354), and group-on-one between group of decision-makers and modeler, for simulation models (Vennix, 1998, 9-13)

The process of interviews has three stages (Gonzalez and Dankel, 1993, 348-354):

1. The kickoff interview, where the rules are stated.
2. The general knowledge gathering interviews where the knowledge engineer or modeler becomes familiar with the domain.

3. The specific knowledge-gathering interviews where the knowledge engineer or modeler tries to elicit deep knowledge about solving problems or proposing policies for a problematic situation.

Other techniques of knowledge elicitation are (1) observation of the expert in his environment of work and (2) intuition. The former can be achieved either quietly or with discussion and even in a simulated environment to observe his actions. The latter consists in an attempt that the knowledge engineer or modeler becomes a pseudo-expert, trying to solve problems faced by an expert. This makes to think and to perceive like an expert or decision-maker as much as possible.

There are several alternatives to the one-on-one interview, each one with its own advantages and disadvantages (Gonzalez and Dankel, 1993, 367-370):

1. The one-on-many
2. The many-on-one
3. The many-on-many

These alternatives help to granulate the knowledge among many individuals. The process gains different perspectives of the object to be modeled. However, the control of the session interview demands special facilitation skills for the knowledge engineer or modeler. He will have to manage time and rhythm of the session and solve conflict among participants, and including other knowledge engineers.

Another aspect is the location. The location of the interviews, in the case of ES, is recommended to start at the expert's workplace. According to project unfold, the interviews are moved to the workplace of the knowledge engineer or modeler. This place used to have fewer interruptions during the sessions. The time recommended is two hours for each interview and never more than three.

Supporting media for recording the proceedings of interviews include audio recording, video recording, direct manual transcription.

Besides traditional methods described above, there are several methods assisted by computers. Three different methods are presented as follows (Gonzalez and Dankel, 1993, 382-405):

1. **Facilitation of the elicitation.** Through the dialogue with an automatic knowledge acquisition tool, questions are asked and responses are organized into a knowledge base.



Repertory grid is the most popular technique for implementing it. This grid assists mainly during the early stages of the knowledge acquisition when the structure is just into the first step of design.

2. **Inductive learning.** The concept is based on learning from examples. Algorithms implemented into a computer generate a minimal classification of trees from examples prepared by an expert. One of the popular algorithms is called ID3 and it has been used in commercial inductive tools. The potential of the tool is when existing examples are already in an electronic format and can be prepared in the requested format of the inductive system.
3. **Automated generation of knowledge from databases.** This technique has been useful for deriving model of engineering systems from CAD drawings. It comprises the examination of a design database for a system schematic, the identification of included components, the resolution of any conflict, and the final creation of a knowledge base that can be used in a model-base reasoning system. This technique although powerful is still limited in its application.

Although these methods do not replace the traditional methods, they provide useful alternatives for some problem domains in several stages of the knowledge acquisition process.

### **2.1.2 The Knowledge Acquisition Bottleneck**

Anyone who has gone through the process of developing a non-trivial knowledge-based system can attest to how painstaking and time-consuming the knowledge engineering process can be.

Indeed, Feigenbaum has named this process as the knowledge acquisition bottleneck process (Feigenbaum, 1979).

The main reasons for this bottleneck situation is the frequent inability of an expert or decision maker to verbalize, or even to be aware of the problem-solving steps he follows. Parsaye (Parsaye, 1988) recognized in psychological studies that this difficulty occurs from the existence of cognitive defenses which makes the knowledge not accessible.

This thesis expects to provide advances of research in this area by eliciting and representing qualitative knowledge using Fuzzy Logic and System Dynamics.

## 2.2 Feedback System Principles as Structure of Knowledge

An organizing structure or theory is essential in any field of knowledge to effectively interrelate our observations, practices and conflicting incidents (Forrester, 1971, Ch. 1, 2.)

Specifically in management systems, a basic structure of principles based on feedback has been developing around system principles since approximately 40 years ago. The concept of “feedback” systems emerged as the long-sought basis for structuring observations of social systems. The theory of systems has slowly been developing in disciplines such as mechanical and electrical engineering. However, such systems are far simpler than social and biological and only in the last decades principles of dynamic interactions in systems have become practical and useful enough to be applied with systems of people (Forrester, 1971).

However, on one hand, such analysis has just been verbal and qualitative. On another hand, mathematics has not been adequate for dealing with essential realities in our important social systems. As a consequence, large number of fragments of knowledge has to be handled and it is still looking for the way to structure this knowledge (Forrester, 1971, 1-2.)

This thesis is based on the assumption that principles and theory of feedback systems are the formal base to study dynamic systems.

There are four main concepts of feedback systems to be presented:

1. System
2. Open and Feedback systems
3. State variable representation
4. Stability

### 2.2.1 System

Even though, there is a number of definitions and interpretations about what a system is, at least everybody agrees with the following basic statement, which is taken as the formal concept in this research.

A system is “*a grouping of parts that operate together for a common purpose.*”

(Forrester, 1971)

The relevance of this claim is a “common purpose.” A system may include physical parts and people as well. A lawn mover is an assembly of physical parts that form a system to cut grass. A

research laboratory is a system of people to develop new products. Management is a system of people to allocate resources and to regulate the activity of a business. A family is a system to live and raise children.

### 2.2.2 Open and Feedback Systems

Systems can be classified as “open” and “feedback.” In an open system, the outputs of the system have no influence on the inputs: there is no feedback. It is said that an open system is not aware of its own performance. In a feedback system, the output of the system does have influence on the inputs: there is feedback. Past behaviors of the system persist at present and control current actions.

Whether a system is open or feedback, it depends on the viewpoint of the observer. This makes sense when the observer defines the purpose of the system (Forrester, 1971, Ch. 1, 6.)

In the same way, the closed boundaries of the system are established by the purpose of the system under observation. The following example presented in (Forrester, 1971, Ch. 1, 6-7) about a lawn mower clarifies these concepts.

1. “The engine, operating without a governor, has no goal for speed. It is an open system in terms of speed regulation. Changing the throttle will change the speed but the speed has no effect on the throttle. Furthermore changes in load will change the speed without causing a throttle adjustment.
2. “Adding a governor produces a feedback system in terms of a constant-speed goal. Changes in load cause changes in speed which produce a compensating change in throttle setting as the governor tries to hold the speed for which it has been set.
3. “But suppose the engine is part of a lawn mower and we change the goal from constant-speed operation to a goal of mowing the lawn. Now, from the broader purpose of cutting grass, the lawn mower is an open system because it has no awareness of what grass has been cut or where to cut next.
4. “By adding the person operating the lawn mower, we again see a feedback system in terms of the goal of cutting a particular lawn. The operator and mower form a feedback system (that is, a goal seeking system) rather than an open system (that is, one not striving for an objective) because the guidance of the mower is in accordance with the pattern of grass already cut.

5. "But if the viewpoint is broaden again to that of the owner of a lawn-care enterprise with a goal of meeting his customer demands, the operator and his lawn mower are properly considered a component of a larger management system. As such, the operator and his equipment represent an open system that is undirected in its sequence of separate tasks.
6. "By adding the management function, instructions arising from customer requirements are introduced as a guide. In terms of the goal of properly scheduled work, the operator, equipment, and owner must be taken together to form a feedback system for the purpose of serving customer lawn-care needs."

Hierarchies of feedback structure and boundaries of the system then arise according to the intention of the observer. A feedback system with a broad purpose may have many components, which in turn may itself be a feedback system in terms of some subordinate purpose.

The simplest structure of a continuous feedback system is represented by:

$$\dot{x}(t) = ax(t)$$

where  $a$  is a scalar. Its graphical representation is shown in Figure 2-1.

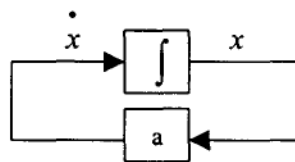


Figure 2-1: The basic feedback structure

Colloquially, it is said, there are two classes of feedback systems: One class is positive feedback and represents and finds the causes of growing that seem to not have limits. A second class, negative feedback represents behaviors of balance and finds causes of fluctuations and instabilities. At the equation above, if  $a > 0$  then the system is positive feedback, if  $a < 0$  then the system is negative feedback, and if  $a = 0$  then there is no movement and it will imply an equilibrium point. In this sense, control theory calls unstable systems to positive feedback systems, and stable systems to negative feedback systems. A formal description of these phenomena is given by studying stability concept in Section 2.1.4.

### 2.2.3 State Variable Representation

The state-space representation has been selected by this research to formally represent a system.

There are five reasons for this:

1. The match between the concepts of state variable  $x(t)$  and rate of change  $dx(t)/dt$  with the ideas of accumulation level and flow rate. Levels and flow rates will play an important role for general analogies that will help us to acquire and represent knowledge of managers and decision-makers.
2. It is a general representation that allows us to handle time varying and nonlinear systems.
3. Its realization and solution can be obtained using the concept of analog-computer simulation.
4. A lot of information can be obtained from the state equations without ever explicitly solving them.
5. First-order differential equations of the state-space description are easily and accurately evaluated on a digital computer.

The general state-representation is given by:

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{u}, t)$$

where  $\mathbf{f}$  is a  $n \times 1$  state nonlinear vector function,  $\mathbf{x}$  is the  $n \times 1$  state vector,  $n$  represents the number of states considered in the system, called the order of the system,  $\mathbf{u}$  is an  $m \times 1$  input vector,  $m$  is the number of inputs, and  $t$  denotes time dependency.

A particular value of the state vector is called a point since it denotes a point in the state space. A solution  $\mathbf{x}(t)$  of the equation provides a trajectory of the system in the state space as  $t$  varies from zero to infinity. This trajectory is referred to as a state-space trajectory or a system trajectory. The dynamics of the system are given by state trajectories.

#### 2.2.3.1 State Variable Description

The state of a physical object is any property of the object, which relates input to output such that knowledge of the input time function for  $t \geq t_0$  and state at time  $t = t_0$  completely determines a unique output for  $t \geq t_0$  (Wiberg, 1971).

The state of an abstract object is a collection of numbers, which together with the input  $\{u(t), t \geq t_0\}$  uniquely determines the output  $\{y(t), t \geq t_0\}$ . A state can be seen as the answer to the question: Given  $\{u(t), t \geq t_0\}$  and the mathematical relationships of the abstract object, what additional information is needed to completely specify  $\{y(t), t \geq t_0\}$ ?

“A state variable, denoted by the vector  $\mathbf{x}(t)$ , is the time function whose value at any specified time is the state of the abstract object at that time... Note the difference in going from a set of numbers to a time function. The state can be a set consisting of an infinity of numbers, in which the state variable is an infinite collection of time functions.” (Wiberg, 1971.)

Let return to the state-space equation, which can be naturally, implemented using analog-computer simulation.

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{u}, t)$$

The vector solution  $\mathbf{x}(t)$  describes the trajectories on time of the internal variables. Elements of  $\mathbf{x}(t)$  are the integrator outputs in any realization. It is clear that if the values of this integrator outputs are known for any given time  $t = t_0$  and the inputs  $\mathbf{u}(t)$  for  $t \geq t_0$  also known then *all* present and future values of the outputs  $\mathbf{y}(t)$ , and integrator outputs (indeed, of any signal anywhere in the simulation) can be calculated.

The advantage of this state-space description is that there is no need to know the past of all the system to establish the present and future behavior.  $\mathbf{x}(t_0)$  provides a sufficient statistical information to calculate the future  $\{t \geq t_0\}$  response to a new input  $\{\mathbf{u}(t), t \geq t_0\}$  without worrying about  $\{\mathbf{u}(t), t \leq t_0\}$ . In this sense,  $\mathbf{x}(t_0)$  is a minimal sufficient statistic.

Colloquially, it is said “the knowledge of the state vector at any time specifies the state or condition of the system at that time” (Kailath, 1980). Therefore, it is natural to call the integrator outputs at any time  $t$  the *state* of the system realization. This interpretation is not restricted to analog-computer realizations but also applies to any set of state-space equations, no matter how they are obtained -as realization of differential equations or as description of physical systems (Kailath, 1980).

The state description of a system is not unique. The system can be described by many different sets of state variables.

### 2.2.3.2 Linear Systems

Linear systems are considered a special class of nonlinear systems.

Commonly, basic structures of knowledge for dynamics are represented by linear systems.

The general linear state-space equations for an  $n$ -states,  $m$ -inputs, and  $k$ -outputs system has the form (Wiberg, 1971).

$$\begin{aligned}\dot{\mathbf{x}} &= \mathbf{A}(t)\mathbf{x}(t) + \mathbf{B}(t)\mathbf{u}(t) \\ \mathbf{y}(t) &= \mathbf{C}(t)\mathbf{x}(t) + \mathbf{D}(t)\mathbf{u}(t)\end{aligned}$$

where  $\mathbf{x}(t)$  is an  $n$ -vector;  $\mathbf{u}(t)$  is an  $m$ -vector;  $\mathbf{y}(t)$  is a  $k$ -vector;  $\mathbf{A}(t)$  is an  $n \times n$  matrix;  $\mathbf{B}(t)$  is an  $n \times m$  matrix;  $\mathbf{C}(t)$  is an  $k \times n$  matrix, and  $\mathbf{D}(t)$  is a  $k \times m$  matrix.

Similarly for discrete time systems:

$$\begin{aligned}\mathbf{x}(n+1) &= \mathbf{A}(n)\mathbf{x}(n) + \mathbf{B}(n)\mathbf{u}(n) \\ \mathbf{y}(n+1) &= \mathbf{C}(n)\mathbf{x}(n) + \mathbf{D}(n)\mathbf{u}(n)\end{aligned}$$

where the dimensions are the same to the continuous time case.

Linear systems are classified as time-varying (LTV) or time-invariant (LTI), according of matrix  $\mathbf{A}$ ,  $\mathbf{B}$ ,  $\mathbf{C}$ , and  $\mathbf{D}$  varies with time or not.

LTI systems are the main concern of linear control theory.

$$\dot{\mathbf{x}}(t) = \mathbf{A}\mathbf{x}(t)$$

This class of systems has quite simple properties, such as:

- Unique equilibrium point if  $\mathbf{A}$  is nonsingular.
- The equilibrium point is stable if all eigenvalues of  $\mathbf{A}$  have negative real parts.
- The transient response is composed of the natural modes of the system.
- The general solution can be solved analytically in the presence of external inputs.
- The principle of superposition is satisfied.
- Asymptotic stability implies bounded-input bounded-output (BIBO) stability.

## 2.2.4 Stability and Instability

First, the concept of equilibrium point is introduced. Many problems concerning stability are formulated with respect to equilibrium points.

Definition “A state  $\mathbf{x}^*$  is an equilibrium state or equilibrium point of the system if once  $\mathbf{x}(t)$  is equal to  $\mathbf{x}^*$ , it remains equal to  $\mathbf{x}^*$  for all future time” (Slotine and Li, 1991, 44.)

Mathematically, it means:

$$\mathbf{0} = \mathbf{f}(\mathbf{x}^*)$$

Nonlinear systems can have several equilibrium points.

For nonlinear systems, a number of refined stability concepts, such as asymptotic stability, exponential stability and global asymptotic stability are needed.

Let  $\mathbf{S}_R$  denotes the sphere defined by  $\|\mathbf{x}\| = R$ , and  $\mathbf{B}_R$  the spherical region (or ball) defined by  $\|\mathbf{x}\| < R$  in state-space.

Definition “The equilibrium state  $\mathbf{x} = \mathbf{0}$  is said stable if, for any  $R > 0$ , there exist  $r > 0$ , such that if  $\|\mathbf{x}(0)\| < r$ , then  $\|\mathbf{x}(t)\| < R$  for all  $t \geq 0$ . Otherwise, the equilibrium point is (unstable)” (Slotine and Li, 1991, 48.)

This concept is called stability in the sense of Lyapunov and mathematically is represented by:

$$\forall R > 0, \exists r > 0, \|\mathbf{x}(0)\| < r \Rightarrow \forall t \geq 0, \|\mathbf{x}(t)\| < R$$

or equivalently

$$\forall R > 0, \exists r > 0, \mathbf{x}(0) \in \mathbf{B}_r \Rightarrow \forall t \geq 0, \mathbf{x}(t) \in \mathbf{B}_R$$

Instability of an equilibrium point refers to a behavior that often leads the system to limit cycles. This is the main qualitative difference between instability and an unstable equilibrium point or the notion of “blowing-up” (all trajectories close to the origin move away to infinity) (Slotine and Li, 1991,48-49.)



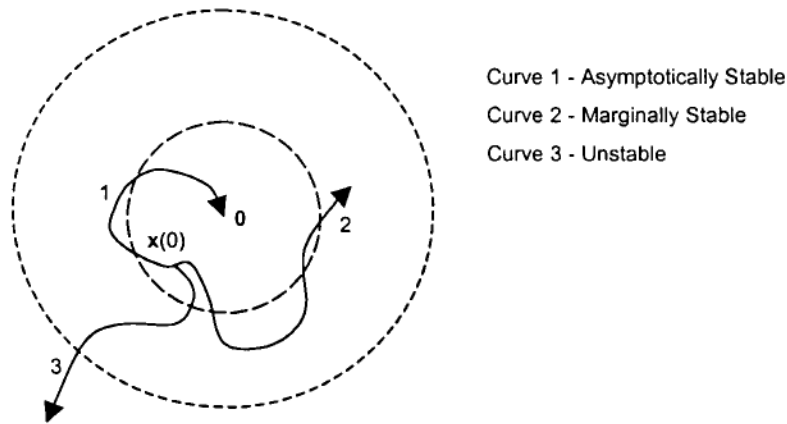


Figure 2-2: Concepts of stability

**Definition** “An equilibrium point  $\mathbf{0}$  is asymptotically stable if it is stable, and if in addition there exist some  $r > 0$  such that  $\|\mathbf{x}(0)\| < r$  implies that  $\mathbf{x}(t) \rightarrow \mathbf{0}$  as  $t \rightarrow \infty$ ” (Slotine and Li, 1991, 50)

When an equilibrium point is stable in the sense of Lyapunov but not asymptotically stable, this point is called marginally stable.

**Definition** “An equilibrium point  $\mathbf{0}$  is exponentially stable if there exist two strictly positive numbers  $\alpha$  and  $\lambda$  such that:

$$\forall t > 0, \|\mathbf{x}(t)\| \leq \alpha \|\mathbf{x}(0)\| e^{-\lambda t}$$

in some ball  $\mathbf{B}_r$  around the origin (Slotine and Li, 1991, 51.)

Note that exponential stability implies asymptotic stability, but not the reverse.

**Definition** “If asymptotic (or exponential) stability holds for any initial states, the equilibrium point is said to be asymptotically (or exponentially) stable in the large. It is also called globally asymptotically (or exponentially) stable (Slotine and Li, 1991, 52.) These concepts on stability are illustrated in Figure 2.2.

For linear time-invariant systems (LTI), asymptotically stability is always global and exponential, and linear instability always implies exponential blow-up. This is the reason why the refined notions of stability introduced here are not encountered in the study of linear systems. These concepts are explicitly needed for nonlinear systems.

## 2.3 Fuzzy Logic for Representing Decision Making Policies

Fuzzy Logic is a paradigm for approximating a functional mapping (Yen, 1999). In the artificial intelligence community, Fuzzy Logic had been traditionally seen just as an approach for managing uncertainty. Also, as a theory to deal with sets with frontiers not strictly exclusive where their elements have partial membership. However, its full potential has emerged as a mapping approach with the characteristic of having an effective trade-off among significance, precision and cost for developing models of complex systems. This focus is what is taken into account in this research to represent the management process, which is considered like a mapping function that convert information into decisions or actions.

Fuzzy logic and Artificial Intelligence has the common objective for developing computational methods to emulate reasoning and problem solving that require human intelligence. However, the big attention on the costs is what makes fuzzy logic distinguishable.

In 1990, Fuzzy Logic, Genetic Algorithms, Neural Networks was grouped into the term of Soft Computing, coined by Zadeh (Zadeh, 1994).

### 2.3.1 Concepts and Principles

In the early 1960's, Lotfi A. Zadeh from the University of California at Berkeley introduced the idea and concept of grade of membership for the elements of a set. In 1965, he published his seminar paper on fuzzy sets (Zadeh, 1965) which lead the emergence of the fuzzy logic technology. The first fuzzy logic controller was published by (Mamdani, 1974) whose model is used to represent the policies of the decision-makers in this research.

Core concepts in fuzzy logic are (1) Fuzzy sets, (2) linguistic variables, (3) possibility distributions, (4) Fuzzy set theory, (5) Fuzzy relations, (6) compositional rule of inference, (7) Fuzzy if-then rules, (8) then Fuzzy mapping rules, (9) Fuzzy implication rules, and (10) Fuzzy graph.

**(1) Fuzzy sets.** A fuzzy set is a generalization to classical set where the elements have degrees of membership. The degree of membership, called membership value, means a degree of belonging to the fuzzy set. It is a real number between 0 and 1. A fuzzy set is characterized by having a set of elements and a membership function that maps these elements of a universe of discourse to their corresponding membership values. The membership function of a fuzzy set A is denoted as  $\mu_A$ .

**(2) Linguistic variables and linguistic values.** Fuzzy sets are associated with a linguistically meaningful term; for example “high” profit and “low” profit. The word profit is the linguistic variable and the adjectives “high” and “low” are its linguistic values. This association of fuzzy sets to linguistic terms offers two important benefits (1) it is easier for human experts to express their knowledge, and (2) the knowledge expressed using linguistic terms is easily comprehensible. These benefits are often related with significant savings in the cost of designing and maintaining a fuzzy logic system. The linguistic values of a linguistic variable can be described as follows (Zadeh, 1975):

1. qualitatively using an expression involving linguistic terms (like an adjective), and
2. quantitatively using a corresponding membership function .

Linguistic terms are useful for communicating ideas and knowledge with human beings. Membership functions are useful for processing numeric input data. A linguistic variable is the equivalent of a symbolic variable in AI and a numeric variable in science and engineering. In general, the values of a linguistic variable can be linguistic expressions of terms and modifiers such as “very,” “more or less” and connectives such as “and,” “or”.

**(3) Possibility distributions.** When a fuzzy set is assigned to a linguistic variable, an elastic constrain on the possible values is assigned, this is called the possibility distribution (Zadeh, 1981). The notion of possible vs. impossible values becomes a matter of degree in this issue. A common question arises about the relationship between possibility distribution with probability distribution. An easy way to understand this relationship is to compare interval-values with probability. The possibility distribution constrains the possible values of a variable without indicating the likelihood that the variable could have for a specific value in the interval. Although, possibility and probability distributions are different, certainly they are related—if a value is impossible, one could infer that the value is improbable. In general, a possibility distribution can be considered as an upper bound on the probability distribution. A complete discussion on this issue is treated in (Bezdek, 1994, cited by Yen, 1999, 155).

Before describing the concept of compositional rule of inference, briefly Fuzzy set theory and Fuzzy relations are explained.

**(4) Fuzzy set theory.** Fuzzy set theory generalizes the conventional set theory (Yen, 1999). In this sense, the axiomatic foundation becomes different from the classical set theory. Specifically, two fundamental laws of Boolean algebra are violated (1) the law of excluded middle  $A \cup \bar{A} = U$  and (2) the law of contradiction  $A \cap \bar{A} = \phi$ . Fundamentally, it means that an

element can partially belongs to a set and to its complement at the same time. As consequence, formula equivalents are not necessarily equivalent for both classical and fuzzy set theories.

The logic operations of intersection and union have multiple choices for the fuzzy conjunction (AND) and the fuzzy disjunction (OR) operations. Two dual and common choices for the fuzzy conjunction and disjunction operations are:

<p>(1) the functions “min” and “max”</p> $\mu_{(A \cap B)}(x) = \min(\mu_{(A)}(x), \mu_{(B)}(x))$ $\mu_{(A \cup B)}(x) = \max(\mu_{(A)}(x), \mu_{(B)}(x))$	<p>(2) the algebraic product and sum</p> $\mu_{(A \cap B)}(x) = \mu_{(A)}(x) \times \mu_{(B)}(x)$ $\mu_{(A \cup B)}(x) = \mu_{(A)}(x) + \mu_{(B)}(x) - \mu_{(A)}(x) \times \mu_{(B)}(x)$
--	--

In general, a fuzzy conjunction operator  $t(x, y)$  and a fuzzy disjunction operator  $s(x, y)$  are a dual pair if they satisfy the following condition:

$$1 - t(x, y) = s(1 - x, 1 - y)$$

which ensures that

$$\overline{A \cap B} = \bar{A} \cup \bar{B}$$

still holds in fuzzy set theory.

Duality is maintained by satisfying the following set of axioms that defines triangular norms or t-norms and also triangular conorms, t-conorms, or s-norms for the fuzzy conjunction and disjunction operators, respectively. They are formally defined as follows:

“A t-norm operator, denoted as  $t(x, y)$ , is a function mapping from  $[0,1] \times [0,1]$  to  $[0,1]$  that satisfies the following conditions for any  $w, x, y, z \in [0,1]$ :

1.  $t(0,0) = 0, t(x,1) = t(1,x) = x$
2.  $t(x, y) \leq t(z, w)$  if  $x \leq z$  and  $y \leq w$  (*monotonicity*)
3.  $t(x, y) = t(y, x)$  (*commutativity*)
4.  $t(x, t(y, z)) = t(t(x, y), z)$  (*associativity*)” (Yen, 1999).

“A t-conorm operator, denoted as  $s(x, y)$ , is a function mapping from  $[0,1] \times [0,1]$  to  $[0,1]$  that satisfies the following conditions for any  $w, x, y, z \in [0,1]$ :

1.  $s(1,1) = 1, s(x,0) = s(0,x) = x$
2.  $s(x, y) \leq s(z, w)$  if  $x \leq z$  and  $y \leq w$  (*monotonicity*)

3.  $s(x, y) = s(y, x)$  (*commutativity*)
4.  $s(x, s(y, z)) = s(s(x, y), z)$  (*associativity*)” (Yen, 1999).

An important property about t-norms and s-norms is that “min” and “max” functions bound all possible choices, respectively. A complete summary about t-norm and s-norm can be found in (Klir and Yuan, 1995).

**(5) Fuzzy relation.** The classical concept of relation is generalized into a matter of degree by the concept of fuzzy relation. For example, a fuzzy relation  $R$  between variables  $x$  and  $y$ , whose domains are  $X$  and  $Y$ , respectively, is defined by a function that maps ordered pairs in  $X \times Y$  to their degree in the relation, which is a number between 0 and 1, this is  $R: X \times Y \rightarrow [0,1]$ . Formally, a fuzzy n-ary relation  $R$  in variables  $x_1, x_2, \dots, x_n$ , whose domains are  $X_1, X_2, \dots, X_n$ , respectively, is defined by a function that maps an n-tuple  $\langle x_1, x_2, \dots, x_n \rangle$  in  $X_1 \times X_2 \times \dots \times X_n$  to a membership value in the interval, this is,  $R: X_1 \times X_2 \times \dots \times X_n \rightarrow [0,1]$ . In this sense, the mapping can be seen as a membership function of a multidimensional fuzzy set.

**(6) Compositional rule of inference.** Definition: “Let  $X$  and  $Y$  be the universes of discourse for variables  $x$  and  $y$ , respectively, and  $X_i$  and  $Y_j$  be elements of  $X$  and  $Y$ . Let  $R$  be a fuzzy relation that maps  $X \times Y$  to  $[0, 1]$  and the possibility distribution of  $X$  is known to be  $\prod_X(x_i)$ . The compositional rule of inference infers the possibility distribution of  $Y$  as follows (Yen, 1999):

$$\prod_Y(y_j) = \bigoplus_{x_i} \left( \prod_X(x_i) \otimes \prod_R(x_i, y_j) \right)$$

The compositional rule of inference depends on the selection of the fuzzy conjunction and fuzzy disjunction operators. It is not uniquely defined and thus different compositional rules of inference can be obtained. Two mostly used are:

1. **max-min composition:**  $\prod_Y(y_j) = \max_{x_i} \left( \min \left( \prod_X(x_i), \prod_R(x_i, y_j) \right) \right)$
2. **max-product composition:**  $\prod_Y(y_j) = \max_{x_i} \left( \prod_X(x_i) \times \prod_R(x_i, y_j) \right)$

**(7) Fuzzy If-Then Rules.** A fuzzy if-then rule is a relation that transforms conditions about linguistic variables to conclusions. From a point of view of knowledge representation, a fuzzy if-then rule is a scheme to capture imprecise knowledge (Yen, 1999). The main feature of reasoning

of this type of knowledge representation is its partial matching capability that enables an inference even when the rule conditions are partially satisfied. To infer a conclusion in a fuzzy rule, the conditions based on the match degree of the input data and the consequent are combined. The higher is the matching degree; the closer is the inferred conclusion to the consequence of the rule.

There are two types of fuzzy rules: (1) fuzzy mapping rules, and (2) fuzzy implication rules. A fuzzy mapping rule is a functional mapping relationship among several inputs and one output using linguistic terms. Its fundamentals come from the fuzzy graph theory. The inference process involves a set of rules, called the fuzzy model, where the antecedent conditions form a fuzzy partition of the input space. The main characteristic when using fuzzy mapping rules is they are designed to work as a group.

A fuzzy implication rule is a generalized logic implication relationship between two logic formulas involving linguistic variables. Its fundamentals come from the generalization of the two-valued logic. The inference of fuzzy implication rules unlike the one of fuzzy mapping rules is performed individually. Certainly, the inference results of the rules can be combined, however the properties of the inference are described in terms of the behavior of individual rules. They are designed to work individually.

This distinction between fuzzy implication rules and fuzzy mapping rules began to be clear in early 1990s when success of fuzzy knowledge-based system in automatic control demanded formal explanations. The difficulty was to explain the “fuzzy implication relation” of rules using the conjunction operator and the aggregation operation in the conclusion of rules using fuzzy disjunction. This difficulty leads to state the fundamental differences between the two types of rules. A detailed description on this theme is found in (Yen and Langari, 1999) and contributions in (Kosko, 1997) and (Dubois and Prade, 1994).

**(8 and 9) Fuzzy Mapping Rules and Fuzzy Implication Rules.** There are two main points on the representation that confuse many scholars about the difference of these rules: (1) both of them are represented as a fuzzy relation between antecedent and consequent variables, and (2) both of their inference schemes are based on the compositional rule of inference. However, there exist a fundamental difference between fuzzy mapping and fuzzy implication rules. This is in the semantic of their inference behavior. The inference behaviors become different when their antecedents are not satisfied.

The central issue is the description of two types of knowledge. By one hand, logic implication is the basis of fuzzy implication rules. They generalize set-to-set implications. The objective is to enable intelligent systems to draw plausible conclusions in a similar way to human reasoning. By the other hand, association knowledge is the essence of fuzzy mapping rules. They generalize set-to-set associations. The objective is to approximate complex relationships, like nonlinear functions, in a balancing form of cost-effective and also in an easily comprehensible form. See (Yen, 1999, 158) for an illustrative example. The formal expressions are declared as follow.

Given

$$r_k \quad (x \text{ is } A) \rightarrow (y \text{ is } B)$$

where A and B are fuzzy sets.

Its corresponding fuzzy mapping rule represented as a fuzzy relation R becomes to express the possibility degrees of association between pairs of input and output values. This is described by (Yen, 1999) as:

$$R_{r_k}(x_i, y_j) = \prod_{r_k} ((x = x_i) \wedge (y = y_j))$$

The possibility distribution is determined from the membership functions of A and B:

$$\begin{aligned} \prod_{r_k} ((x = x_i) \wedge (y = y_j)) &= t((x_i \text{ is } A) \wedge (y_j \text{ is } B)) \\ &= \mu_A(x_i) \otimes \mu_B(y_j) \end{aligned}$$

where  $\prod$  denotes the possibility distribution,  $\otimes$  a fuzzy conjunction operator, and  $t$  the truth value of a formula.

The corresponding fuzzy implication rule represented as a fuzzy relation R becomes to express the possibility degrees of implication between pairs of input and output values. This is described by (Yen, 1999) as:

$$R_l(x_i, y_j) = \prod_l ((x = x_i) \rightarrow (y = y_j))$$

The possibility distribution is determined from the membership functions of A and B.

$$\prod_{r_k} ((x = x_i) \rightarrow (y = y_j)) = t((x_i \text{ is } A) \rightarrow (y_j \text{ is } B))$$

(10) **Fuzzy Graph** (reproduced from Yen, 1999). Fuzzy mapping rules have its foundation in fuzzy graph (Zadeh, 1994) cited in (Yen, 1999). A fuzzy graph  $f^*$  from  $X$  to  $Y$  is a union of

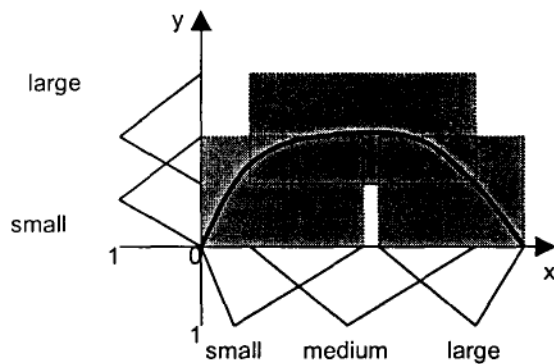
Cartesian products involving linguistic input-output associations. Let  $f^*$  be a fuzzy graph described by a set of fuzzy mapping rules in the form of “if  $x$  is  $A_i$  then  $y$  is  $B_i$ ”. The fuzzy graph can be expressed mathematically (Yen, 1999) as:

$$f^* = \cup_i A_i \times B_i$$

In  $f^*$ ,  $\cup$  denotes the fuzzy disjunction. The Cartesian product of  $A$  and  $B$ , denoted by  $A \times B$ , is defined as

$$\mu_{A \times B}(u, v) = \mu_A(u) \otimes \mu_B(v)$$

An expression of the form  $A \times B$  where  $A$  and  $B$  are words (fuzzy sets) is referred as a Cartesian granule (Zadeh, 1996). Figure 2-3 depicts a fuzzy graph consisting of three fuzzy mapping rules:



- f: IF X is small THEN Y is small.  
IF X is medium THEN Y is large.  
IF X is large THEN Y is small.

The resulting fuzzy graph is basically a fuzzy relation.

Figure 2-3: Fuzzy graph approximation by a set of fuzzy mapping rules

The inference (i.e. interpolative reasoning) of such a set of fuzzy mapping rules is also based on compositional rule of inference introduced earlier. Given an input “ $x$  is  $A$ ” to the model, the inferred output of the model is a possibility distribution  $B'$  of  $y$ :

$$B' = A \circ f^* = A \circ (\cup_i A_i \times B_i)$$

where  $f^*$  represents the fuzzy graph of a given fuzzy model,  $\circ$  denotes the composition rule of inference.



## 2.3.2 Fuzzy Models

### 2.3.2.1 Ordinary Fuzzy Model

Ordinary fuzzy models have the forms:

$$L^i : \text{if } x_1 \text{ is } A_1^i \text{ and } \dots x_n \text{ is } A_n^i \text{ then } y \text{ is } C^i$$

where  $L^i$  ( $i = 1, 2, \dots, l$ ) denotes the  $i$ -th implication,  $l$  the number of fuzzy implications,  $A_j^i$  and  $C^i$  are fuzzy sets,  $x_j$  is the  $j$ -th input variable and  $y$  is the output variable. Let for simplicity to write the membership function of the fuzzy set  $A_i$  as  $A_i(x)$ . So from (1), the fuzzy relational equations are described by:

$$C^i = R^i \circ (A_1^i \times \dots \times A_n^i) \quad i = 1, 2, \dots, l$$

where  $\circ$  denotes the max-min composition and  $\times$  the Cartesian product. If Mamdani's method is applied (Mamdani, 1974), the fuzzy relations  $R^i$  follow:

$$R^i = \int_{x_1 \times x_2 \times \dots \times x_n \times y} \min(A_1^i(x_1), A_2^i(x_2), \dots, A_n^i(x_n), C^i(y)) / (x_1, x_2, \dots, x_n, y)$$

and the final relation  $R$  is calculated by:

$$R = \bigcup_{i=1}^l R^i$$

where  $\bigcup$  is the union operator.

### 2.3.2.2 Fuzzy Model of Takagi and Sugeno

Fuzzy model of Takagi and Sugeno (Takagi and Sugeno, 1985) has the form:

$$L^i : \text{if } x_1 \text{ is } A_1^i \text{ and } \dots x_n \text{ is } A_n^i \text{ then } y^i = c_0^i + c_1^i x_1 + \dots + c_n^i x_n$$

where  $L^i$  ( $i = 1, 2, \dots, l$ ) denotes the  $i$ -th implication,  $l$  is the number of implications,  $A_j^i$  is a fuzzy set where membership functions are of convex type and formed by straight lines,  $c_j^i$  is a consequent parameter,  $x_j$  is the  $j$ -th input variable, and  $y^i$  the output variable of the  $i$ -th implication.

The final output of the fuzzy model is inferred by taking the weighting average of the outputs  $y^i$ 's.

$$y = \frac{\sum_{i=1}^l w^i y^i}{\sum_{i=1}^l w^i}$$

the weighted  $w^i$  implies the overall truth value of the premise of the  $i$ -th implication and it is calculated as:

$$w^i = \prod_{k=1}^n A_k^i(x_k)$$

Two main advantages are observed by using Takagi and Sugeno's model with respect to ordinary piecewise linear approximation:

Reduction of the number of piecewise linear relations which becomes crucial in a multidimensional case.

Linguistic conditions such as " $x_1$  is small and  $x_2$  is big" can be mapped to linear relations. Thus qualitative and uncertain knowledge as observed and described by man can be used.

### 2.3.3 Fuzzy Knowledge-based Systems

A Fuzzy Knowledge-Based System (FKBS) is a fuzzy model for approximating a functional mapping from input crisp signals to crisp output signals.

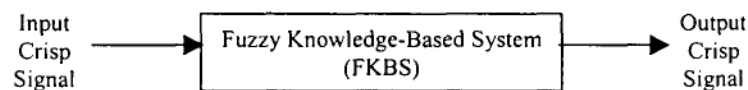


Figure 2-4: FKBS as approximated mapping function

A FKBS is formed by three basic processes: (1) fuzzification, (2) Approximating Reasoning Engine, and (3) defuzzification.

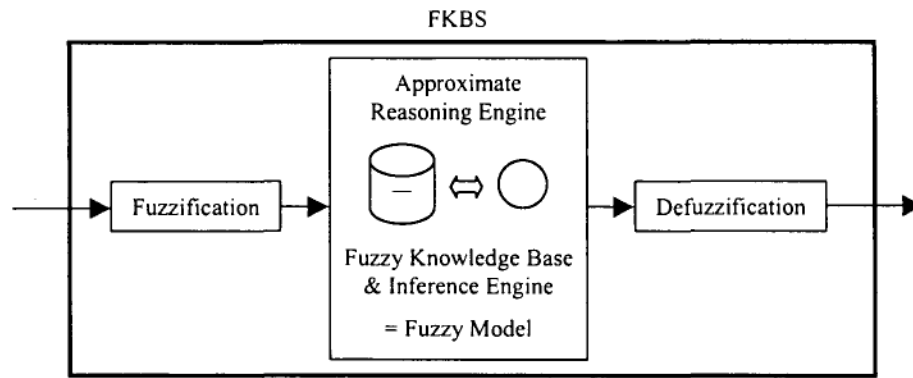


Figure 2-5: Parts of a FKBS

**Fuzzification.** A set of numerical crisp values is mapped to a set of numerical membership values according to defined fuzzy sets (Ghalia and Wang, 2000, 387.)

**Approximate Reasoning Engine.** Conclusions are derived from premises. Both conclusions and premises are given in the format of numerical membership values. The process is carried out through the use of a Fuzzy Knowledge Base (set of fuzzy if-then rules). The rules are acquired from the experts or decision-makers in a conventional knowledge engineering process. The reasoning process follows two steps. Firstly, the Approximate Reasoning Engine (ARE) evaluates the production rules. Secondly, it aggregates the fuzzy conclusions resulting from all the rules into one fuzzy conclusion set. The flow of the information between the Fuzzification and ARE is unidirectional (Ghalia and Wang, 2000, 388.)

**Defuzzification.** The fuzzy conclusion set described by numerical values membership values is mapped to numerical crisp values, which reflects the action that has to be taken (Ghalia and Wang, 2000, 388.)

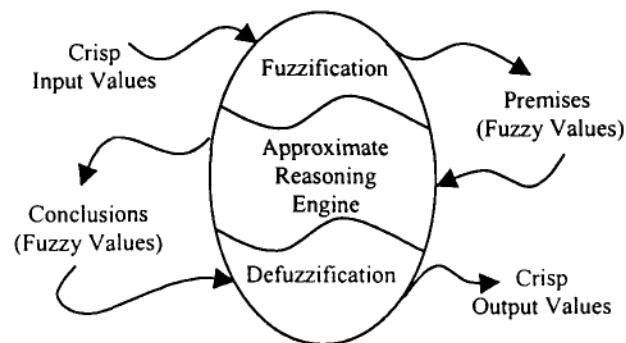


Figure 2-6: Information flow diagram of a FKBS

The FKBS will act as a Virtual Decision-Maker whose actions will response to the policies extracted from decision-makers in the knowledge acquisition process.

### 2.3.4 Design of a Virtual Decision-Maker based on Fuzzy Knowledge-Based Systems

Consider a stable process (business process in this case) where the system structure is modeled as Multi Input – Multi Output (MIMO) nonlinear system of order two. The dimension is defined to be 2 x 2 at this moment for sake of the explanation.

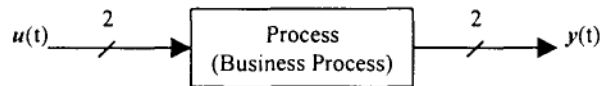


Figure 2-7: Business process as MIMO system

The objective is to design a FKBS to act as a Virtual Decision-Maker so that satisfies the following four criteria:

1. Stable equilibrium points may be reached and sustained at all time.
2. Equilibrium points are exponentially stable.
3. Steady-state deviations between perceived and desired conditions can be eliminated.
4. Cost of the model development is requested as small as possible.

The design considers:

1. The selection of the variables in which decisions can be implemented.
2. The selection of variables as business indicators to observe.
3. The fuzzy knowledge base.
4. The definition of the membership functions.

The FKBS can be realized using several structures. Some of them are shown in Figure 2-5 (Viljamaa and Koivo, 1993).

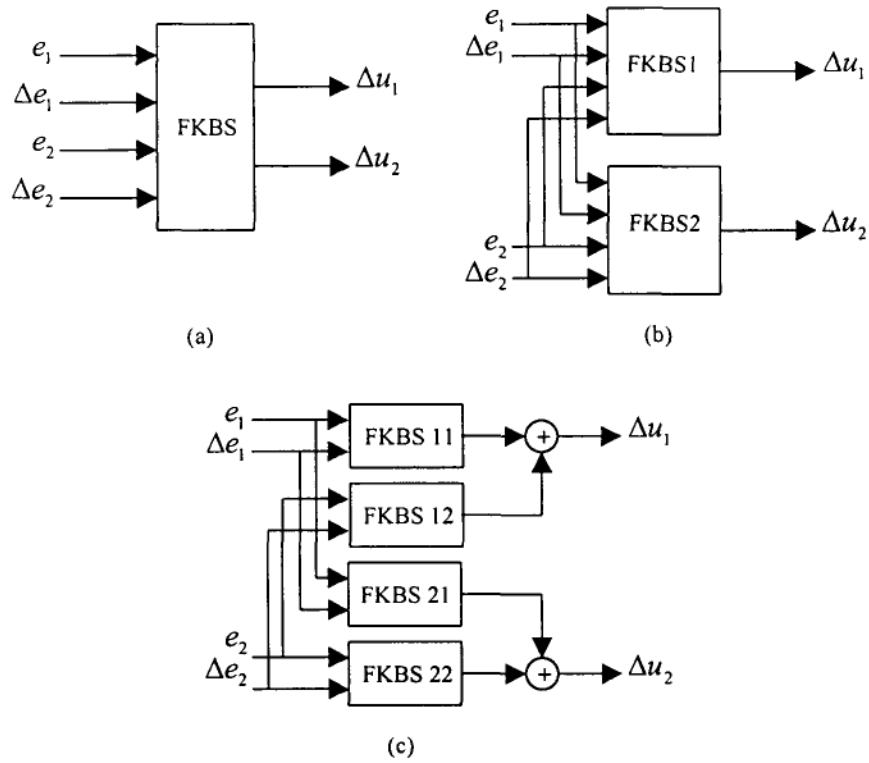


Figure 2-8: MIMO 2 x 2 structures for FKBS

The input variables are deviations ( $e_i$ ) and tendency deviations ( $\Delta e_i \approx \dot{e}_i$ ). The output variables are increments in decision variables ( $\Delta u_i$ ).

The membership functions considered for each input variable have the form:

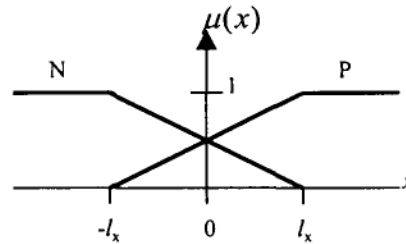


Figure 2-9: Membership function for input variables

Singletons are selected to be the membership function of the output variables.

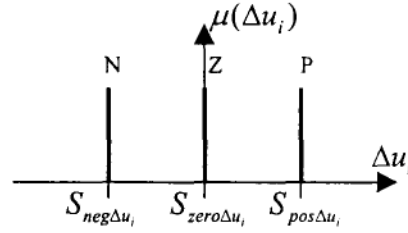


Figure 2-10: Membership function for output variables

The FKBS structure has the form:

$$\Delta \mathbf{u}(k) = \mathbf{f}(\mathbf{e}(k), \dot{\mathbf{e}}(k))$$

where  $\mathbf{f}(\cdot) \in \mathfrak{R}^2$  is the approximate mapping function which transforms information into action.

$$\mathbf{e}(k) = \begin{bmatrix} e_1(k) \\ e_2(k) \end{bmatrix} = \begin{bmatrix} \text{Desired conditions}_1(k) - \text{Perceived conditions}_1(k) \\ \text{Desired conditions}_2(k) - \text{Perceived conditions}_2(k) \end{bmatrix}$$

$$\dot{\mathbf{e}}(k) \approx \Delta \mathbf{e}(k) = \begin{bmatrix} e_1(k) - e_1(k-1) \\ e_2(k) - e_2(k-1) \end{bmatrix}$$

dimensions of  $\mathbf{e}(\cdot)$  are same dimensions of  $\mathbf{y}(t)$ .

Two fuzzy sets for each input variable are used and defined for the interval  $-l_x < x < l_x$  as it shown in Fig. 2-9.

$$\mu_{positive} = \begin{bmatrix} \mu_{pos1} \\ \mu_{pos2} \\ \mu_{pos3} \\ \mu_{pos4} \end{bmatrix} = \begin{bmatrix} (e_1 + l_{e_1})/2l_{e_1} \\ (\Delta e_1 + l_{\Delta e_1})/2l_{\Delta e_1} \\ (e_2 + l_{e_2})/2l_{e_2} \\ (\Delta e_2 + l_{\Delta e_2})/2l_{\Delta e_2} \end{bmatrix}$$

$$\mu_{negative} = [\mu_{neg1} \ \mu_{neg2} \ \mu_{neg3} \ \mu_{neg4}]^T = [1 \ 1 \ 1 \ 1]^T - \mu_{positive}$$

The outputs of the FKBS are changes  $\Delta \mathbf{u}(k)$  in the decision variables. Final decision is set in action as  $\mathbf{u}(k)$ :

$$\mathbf{u}(k) = \begin{bmatrix} u_1(k-1) + \Delta u_1(k) \\ u_2(k-1) + \Delta u_2(k) \end{bmatrix}$$

The complete rule-base has 16 rules and it is shown in Table 2-1. Rules has the following form:

Rule 6.

*if ( $e_1$  is N) and ( $\dot{e}_1$  is P) and ( $e_2$  is N) and ( $\dot{e}_2$  is P) then  $\Delta u_1$  is Z*

*if ( $e_1$  is N) and ( $\dot{e}_1$  is P) and ( $e_2$  is N) and ( $\dot{e}_2$  is P) then  $\Delta u_2$  is Z*

Generally, consequences for rules 6, 7, 10, and 11 can be filled before hand since perceived conditions are going toward the desired conditions and decisions do not need changes (Viljamaa and Koivo, 1993).

**Table 2-1: Basic rule base**

Rule	$e_1$	$\Delta e_1$	$e_2$	$\Delta e_2$	$\Delta u_1$	$\Delta u_2$
1.	N	N	N	N		
2.	N	N	N	P		
3.	N	N	P	N		
4.	N	N	P	P		
5.	N	P	N	N		
6.	N	P	N	P	Z	Z
7.	N	P	P	N	Z	Z
8.	N	P	P	P		
9.	P	N	N	N		
10.	P	N	N	P	Z	Z
11.	P	N	P	N	Z	Z
12.	P	N	P	P		
13.	P	P	N	N		
14.	P	P	N	P		
15.	P	P	P	N		
16.	P	P	P	P		

The other consequences depend on specific process in which the FKBS is applied. However, based on a basic analysis, it can be reached to the conclusion that the consequences of pair of rules 2-3, 5-9, 8-12, and 14 y 15 are the same.

**Table 2-2: Conclusions for the basic rule base**

	Conclusion	From rule(s)
i)	$\min\{\mu_{neg1}, \mu_{neg2}, \mu_{neg3}, \mu_{neg4}\}$	1
ii)	$\max\left\{\begin{array}{l} \min\{\mu_{neg1}, \mu_{neg2}, \mu_{neg3}, \mu_{pos4}\} \\ \min\{\mu_{neg1}, \mu_{neg2}, \mu_{pos3}, \mu_{neg4}\} \end{array}\right\}$	2 and 3
iii)	$\min\{\mu_{neg1}, \mu_{neg2}, \mu_{pos3}, \mu_{pos4}\}$	4
iv)	$\max\left\{\begin{array}{l} \min\{\mu_{neg1}, \mu_{pos2}, \mu_{neg3}, \mu_{neg4}\} \\ \min\{\mu_{pos1}, \mu_{neg2}, \mu_{neg3}, \mu_{neg4}\} \end{array}\right\}$	5 and 9
v)	$\max\left\{\begin{array}{l} \min\{\mu_{neg1}, \mu_{pos2}, \mu_{neg3}, \mu_{pos4}\} \\ \min\{\mu_{neg1}, \mu_{pos2}, \mu_{pos3}, \mu_{neg4}\} \\ \min\{\mu_{pos1}, \mu_{neg2}, \mu_{neg3}, \mu_{pos4}\} \\ \min\{\mu_{pos1}, \mu_{neg2}, \mu_{pos3}, \mu_{neg4}\} \end{array}\right\}$	6, 7, 10, and 11
vi)	$\max\left\{\begin{array}{l} \min\{\mu_{neg1}, \mu_{pos2}, \mu_{pos3}, \mu_{pos4}\} \\ \min\{\mu_{pos1}, \mu_{neg2}, \mu_{pos3}, \mu_{pos4}\} \end{array}\right\}$	8 and 12
vii)	$\min\{\mu_{pos1}, \mu_{pos2}, \mu_{neg3}, \mu_{neg4}\}$	13
viii)	$\max\left\{\begin{array}{l} \min\{\mu_{pos1}, \mu_{pos2}, \mu_{neg3}, \mu_{pos4}\} \\ \min\{\mu_{pos1}, \mu_{pos2}, \mu_{pos3}, \mu_{neg4}\} \end{array}\right\}$	14 and 15
ix)	$\min\{\mu_{pos1}, \mu_{pos2}, \mu_{pos3}, \mu_{pos4}\}$	16

Thus each pair of rules can be combined to one rule. For example, the new rule for the pair of rules 2 and 3 will have the form:



$$\begin{aligned}
& \text{if} \\
& \{(e_1 \text{ is } N) \text{ and } (\dot{e}_1 \text{ is } N) \text{ and } (e_2 \text{ is } N) \text{ and } (\dot{e}_2 \text{ is } P)\} \\
& \text{or} \\
& \{(e_1 \text{ is } N) \text{ and } (\dot{e}_1 \text{ is } N) \text{ and } (e_2 \text{ is } P) \text{ and } (\dot{e}_2 \text{ is } N)\} \\
& \text{then} \\
& \{\Delta u_1 \text{ is some linguistic value of } \Delta u_1\} \\
& \text{and} \\
& \{\Delta u_2 \text{ is some linguistic value of } \Delta u_2\}
\end{aligned}$$

When operations *min* and *max* are applied to realize the *and* and *or* operations the fuzzy reasoning can be resumed as shown in Table 2-2.

This set of conclusions may be general for both outputs of the FKBS and also for different process since the same results were reached by different methods and context by (Viljamaa and Koivo, 1993) and by this research.

Depending on the assigned singletons to each conclusion, other *max* operations might be required to obtain the fuzzy conclusion set. Once obtained it, the defuzzification is carried out by the equation:

$$\Delta \mathbf{u}(k) = \begin{bmatrix} \Delta u_1(k) \\ \Delta u_2(k) \end{bmatrix} = \begin{bmatrix} \alpha \mu_{neg\Delta u_1} & \alpha \mu_{zero\Delta u_1} & \alpha \mu_{pos\Delta u_1} & 0 & 0 & 0 \\ 0 & 0 & 0 & \beta \mu_{neg\Delta u_2} & \beta \mu_{zero\Delta u_2} & \beta \mu_{pos\Delta u_2} \end{bmatrix} \begin{bmatrix} S_{neg\Delta u_1} \\ S_{zero\Delta u_1} \\ S_{pos\Delta u_1} \\ S_{neg\Delta u_2} \\ S_{zero\Delta u_2} \\ S_{pos\Delta u_2} \end{bmatrix}$$

where  $\alpha = 1 / (\mu_{neg\Delta u_1} + \mu_{zero\Delta u_1} + \mu_{pos\Delta u_1})$  and  $\beta = 1 / (\mu_{neg\Delta u_2} + \mu_{zero\Delta u_2} + \mu_{pos\Delta u_2})$  and

$\mu_{neg\Delta u_i}$ ,  $\mu_{zero\Delta u_i}$ ,  $\mu_{pos\Delta u_i}$  are the values of the membership function of the *i*-th fuzzy set of the output variables and  $S_{neg\Delta u_i}$ ,  $S_{zero\Delta u_i}$ ,  $S_{pos\Delta u_i}$  are the places of the singletons.

A tuning method for multivariable physical systems with this FKBS structure can be found in (Viljamaa and Koivo, 1993).

## 2.4 System Dynamics as Knowledge Acquisition Method

System dynamics was developed by Jay W. Forrester at the Sloan School of Management at the Massachusetts Institute of Technology in the second half of the 1950's. Forrester joined the Sloan School since its foundation in 1956.

During his first year at Sloan School, Forrester was devoted to the study of operations research (OR) (also called management science), which aims to support managerial decision making using scientific and mathematical methods. Three of the conclusions of this study are (Forrester, 1975): (1) OR neglected nonlinear phenomena, (2) OR was an open-loop approach of the decision making process (decisions are not considered affected by the decisions themselves), and (3) OR was ineffective in helping to solve broad strategic management problems.

As consequence, connections between electrical engineering and management started. This originated the study of decision making in social systems from a perspective of information feedback theory. Forrester proposed the closed-loop thinking in the sense that the decisions affect the environment, and changes of the environment in turn provide the inputs to decisions that will affect the environment again.

One problem emerged. Since the nonlinear relationships between system elements would be considered, many analytical solutions of the model equation would be unfeasible. As an alternative, Forrester suggested the use of analog simulation principles using digital computers. The computer language DYNAMO was developed to accomplish such a task as well. The approach then became an experimental approach based on information feedback theory to simulate social systems with the support of digital computers.

Two distinguishing elements characterize the approach: (1) closed-loop thinking and (2) a firm claim that social systems can productively studied as information feedback control systems, i.e. systems where a decision affects the environment which in turn affects the decision (Vennix, 1998).

The approach was firstly applied to corporate problems with the name of Industrial dynamics. It was introduced to the management world by first time in the article (Forrester, 1958) in the *Harvard Business Review*. This article demonstrated the applicability of the method. The article contains the fundamental ideas and building blocks, which would remain without changes over the next decades.

The name evolved from *Industrial Dynamics* to *System Dynamics* because of the application of the method to a large variety of problems. Bibliography written by Forrester illustrates the fact: *Industrial Dynamics* (Forrester, 1961), *Urban Dynamics* (Forrester, 1969), *World Dynamics* (Forrester, 1973), and *Business Dynamics* (Sterman, 2000)<sup>1</sup>. Among the current fields of application are included: commodity production cycles, research and development, inventory control, corporate policy studies, economic fluctuations, dynamics of ecosystems, energy, health care delivery, and project management to mention just a few.

The principles of the discipline are explained as follows.

### 2.4.1 Concepts and Principles

Definition: "System dynamics deals with how things change through time, which includes most of what most people find important. It uses computer simulation to take the knowledge we already have about details in the world around us and to show why our social and physical systems behave the way they do. System dynamics demonstrates how most of our own decision-making policies are the cause of the problems that we usually blame on others, and how to identify policies we can follow to improve our situation" *Jay W. Forrester*.<sup>2</sup>

A System Dynamic Model is the representation of a set of policies in action. Policies understood in this context as the rules that govern decisions.

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<sup>1</sup> Professor John D. Sterman is currently Director of the System Dynamics Group at M.I.T., Sloan School of Management, U.S.A.

<sup>2</sup> This was the answer of Prof. Forrester to the System Dynamic e-mail list concerning to an open enquiry of defining what System Dynamics is to somebody during an elevator ride, 1997.

### 2.4.1.1 Structure for Modeling

The structure for modeling systems is formed by four hierarchical levels. Organized from major to subordinate components, it follows:

(I) The closed system responsible of generating the behavior that is created within a boundary and not dependent on external inputs (exogenous variables).

(A) The feedback loops as the structural units to assemble systems.

(1) The levels (or state variable of the system).

(2) The rates (or policies).

(a) The goal.

(b) The apparent condition, which is compared to the goal.

(c) The discrepancy between the goal and apparent condition.

(d) The resulting action from the discrepancy.

### 2.4.1.2 Closed Boundary

The central issue is systems as the cause of dynamic behavior.

The focus is on the interactions within the system. So fluctuation (instability), growth (unstability), and goal-seeking changes (stability) are produced by the interactions of the system component.

Principles of systems are cited below from (Forrester, 1971). The assigned number of the principles is respected to the original text.

*“Principle 4.1.1. Closed boundary.*

*“In concept a feedback system is a closed system. Its dynamic behavior arises within its internal structure. Any interaction which is essential to the behavior mode being investigated must be included inside the system boundary”* (Forrester, 1971).

Forrester refers to *the interactions* in the same sense as control theory refers to *the modes* of a system. Closed boundary means that it is considering dominants or significant dynamics of the system, it does not say something about material or energy exchange between elements inside and outside physical boundaries of the system.

### 2.4.1.3 Feedback Loop. Structural Unit of Systems

Feedback loop is the basic building block within the system boundary. It comes to be obvious, if it is thought on the very basic equation of movement  $\dot{x}(t) = ax(t)$ , where  $a$  is a constant scalar. Its block diagrams representation is a feedback loop and is shown in Figure 2-11.

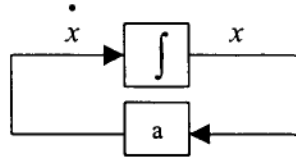


Figure 2-11: Basic building block

*“Principle 4.2-2. Feedback loop—the structural element of systems.*

*“The feedback loop is the basic structural element in systems. Dynamic behavior is generated by feedback. The more complex systems are assemblies of interacting feedback loops.” (Forrester, 1971).*

Forrester discussed this concept at a level of decision process. Considering a decision process that one that controls any system action. Which implies all natural process as well, not only human decision making.

*“Principle 4.2-1. Decisions always within feedback.*

*“Every decision is made within a feedback loop. The decision controls action, which alters the system levels, which influence the decision. A decision process can be part of more than one feedback loop” (Forrester, 1971).*

### 2.4.1.4 Levels and Rates

Systems are formed by feedback loops. Feedback loops are formed by two fundamental type of variables at a lower hierarchy: the levels, and the rates variables.

Levels and rates are the nouns and verbs in a language for representing movement. They are the two primary building blocks for representing the structure of any feedback loop. Both of them always come together. There is no one without the other. If a level of accumulation appears then it was the result of some rate, and vice versa. Activities leaves “tracks”, which in turn, stimulate further activities.

In our basic equation of movement  $\dot{x} = ax(t)$ ,  $\dot{x}$  is the rate and  $x(t)$  is the level.

*“Principle 4.3-1. Levels and rates as loop substructure.*

*A feedback loop consists of two distinctly different types of variables: the levels (states) and the rates (actions). Except for constants, these two are sufficient to represent a feedback loop. Both are necessary” (Forrester, 1971).*

**Levels:** Level means level of accumulation of something. Accumulation of food in one’s stomach, money in a bank, knowledge in a team, love in a heart. The level variables represent the accumulations in a system.

At any time, accumulations indicate how things are going. They indicate the state of the system. If the stomach is too full, one is uncomfortable. If the motivation of a team is high, the team gets good performance.

The level variables (or state variables according to control theory) contains the minimal statistical information of the system condition needed at any particular time to define the dynamics behavior of the system given the input signals for time  $t, t \geq 0$ . The behavior is uniquely defined.

*“Principle 4.3-2. Levels are integration.*

*“The levels integrate (or accumulate) the results of action in a system. The level variable can not change instantaneously. The levels create system continuity between points in time” (Forrester, 1971).*

The reason that accumulations matter in this context is that it enables and inhibits actions. It acts both as resources and constraints. As resources, it enables actions. For example, it is possible to continue reading this paragraph because of the energy and knowledge reserves in the body. Nothing would be done without accumulations.

It is important to denote two kinds of resources: Consumable and Catalysts. Energy, money, gasoline, and water are instances of consumable. Knowledge, love, self-confidence- and commitment are instances of catalysts. The difference is that during the action, the formers are consumed and the latter not. Energy resources and knowledge are the two resources that enable cumulative activity in Figure 2-12. The connectors running from “Energy Reserves” and “Knowledge” to the “activity” represent such relations. The flow of “activity”, in turn, results in the “consuming” of “Energy Reserves” and the generation of “learning” which builds up “Knowledge”. The wires connecting “activity” to “consuming” and “learning” represents such relations. As constraints, the resources block the action. Accumulation of smoke in a room makes

it difficult to breathe. Accumulation of frustration often inhibits effective work. In any case, levels of accumulation affect flows or activities.

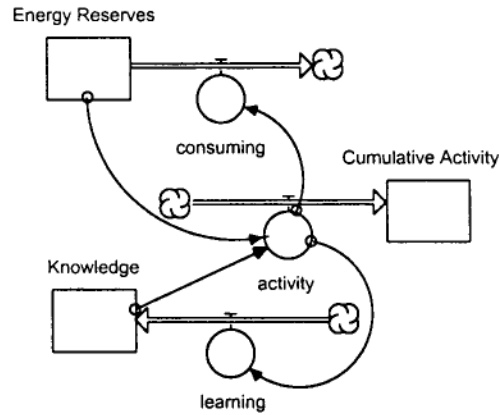


Figure 2-12: Stocks can act as consumables and catalysts (Figure from HPS, 1996, Ch. 2, 3)

Let add an exogenous variable to our basic equation of movement:

$$\dot{x} = ax(t) + bu(t)$$

where  $u(t)$  is the exogenous variable and for the sake of explanation at this moment  $a$  and  $b$  are constants.

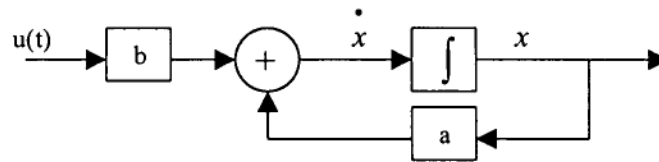


Figure 2-13: Feedback with an exogenous variable

Looking at its block diagram representation in Figure 2-13, it can be observed that computing level values only involves the integration of its rate  $\dot{x}$ . It does not involve any other level variable. So, level variables accumulate flows described by rate variables. Naturally, it can be said now that a level equation performs the process of integration defined in calculus. Thus, the computation of a new value of a level requires past values of the level variable itself, the rates that cause the level changes, and the time interval used by the integral method.

*"Principle 4.3-3. Levels are changed only by the rates.*

*"A level variable is computed by the change, due to rate variables, that alters the previous value of the level. The earlier value of the level is carried forward from the previous period. It is altered by rates that flow over the intervening time interval. The present value of a level variable can be computed without the present or previous value of any other level variables."*  
(Forrester, 1971).

*"Principle 4.3-4. Levels and rates not distinguished by units of measure.*

*"The units of measure of a variable do not distinguish between a level and a rate. The identification must recognize the difference between a variable created by integration and one that is a policy statement in the system."*  
(Forrester, 1971).

**Rates:** The rate variables indicate how fast the level variables change. Indeed, they are the slopes of the level variables. The relevant meaning is that rates are the policy statements that describe the action in a system. They are the action output of a decision point based on the information inputs to that decision.

"A policy is a formal statement giving the relationship between information inputs and resulting decision flow. Policies are often referred to in the literature as decision rules." (Forrester, 1994). Policies are rules that govern decisions (Ackoff, 1992). In system dynamics, the word "policy" is used as a broad term to describe how decision processes convert information into action.

A rate equation is the mathematical expression of a policy statement. "Rate equation" and "policy" have, as used here, the same meaning. That is, a rate equation tells how the information inputs are used to generate decisions. In the same sense, "decision streams" and "actions streams" are considered equivalent, as used, the decision and the action are one and the same. If it would preferable to consider some delay and discrepancy between the deciding and the doing then it will be necessary to involve the usage of level variables.

In industrial organizations, some policies are reduced to writing so they are converted in formal policies with the purpose of guiding the subordinates. However, most guiding policies are informal but fully as influential. Informal policies are constructed within organization and personal interests and result from habits, conformities, social pressures, ingrained concepts of goals, awareness of power centers, etc. (Forrester, 1994).



A new value of rate depends only on values of level variables and constants, neither past rate nor integral time interval.

*“Principle 4.3-5. Rates are not instantaneously measurable.*

*“No rate of flow can be measured except as an average over a period of time. No rate can, in principle, control another rate without an intervening level variable.” (Forrester, 1971).*

*“Principle 4.3.6. Rates depend only on levels and constants.*

*“The value of a rate variable depends only on constants and on present values of level variables. No rate variable depends directly on any other rate variable. The rate equations (policy statements) of a system are of simple algebraic form; they do not involve time or the solution interval; they are not dependent on their own past values.” (Forrester, 1971).*

*“Principle 4.3-7. Level variables and rate variables must alternate.*

*“Any path through the structure of a system encounters alternating level and rate variables.” (Forrester, 1971).*

#### **2.4.1.5 Goal, Apparent Condition, Discrepancy, and Action**

The last hierarchy of structure corresponds to the internal structure of rate equations. For level equation, it does not seem to be useful to establish subdivision. The level equation is a straightforward arithmetic sum of its previous value and the current change in the level.

But the rate equations contain an important internal structure. The structure represents the fundamental decision-making process. The structure is shown in Figure 2-14.

The decision-making process consists of three parts (Forrester, 1994):

1. Definition of a set of concepts that describe desired conditions.
2. Observation of what seems to be the actual conditions.
3. Generation of corrective actions to bring apparent toward desired conditions.

The components are referred to as sub-structure of a system, and they are:

1. A goal.
2. An apparent or observed condition of the system.
3. A discrepancy between goal and apparent condition.
4. An action generated based on the discrepancy.

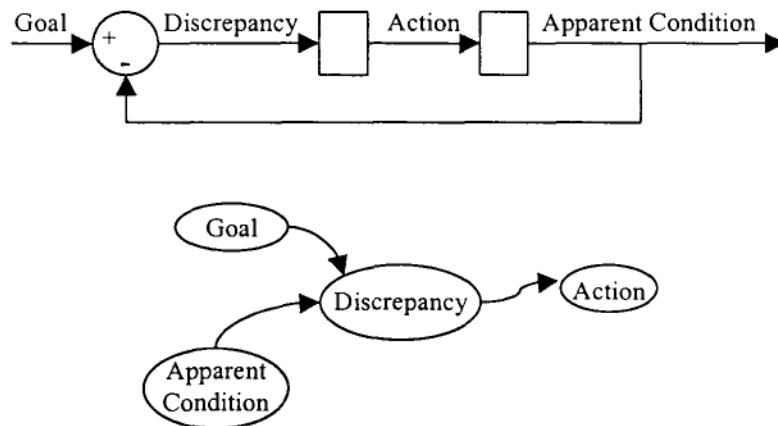


Figure 2-14: Structure of the basic decision making process

In negative feedback loops (or balanced loops), the rate equation generates actions to reduce discrepancies between apparent and desired conditions. The characteristic effect is a state of balance. However, it has to be said that this last statement is not general. It can be proved that systems with high delays and big corrective actions are not able to reach a state of balance.

In positive feedback loops (or reinforcement loops), the rate equation generates actions that bring the system to an ever-increasing growth, until the system reach a limit.

## 2.4.2 Graphical Computer Language

The roots of the following graphical computer language come from the conceptual framework and methodology of system dynamics.

The relevance of this language is the use of two the main concepts: accumulations (levels) and rate of change of accumulations (flow rates) to represent feedback structures. These two concepts have been well known for a long time in control theory as state variables and as its rate of change, respectively. The novel contribution of Professor Forrester was to put them along with a experimentation process discipline with simulators in a way that yielded an approach with practical applications to a wide range of disciplines.

### 2.4.2.1 The Alphabet

Five symbols form the alphabet of the graphical computer language: stocks (levels), flows (rates), converters, connectors and system boundaries (sources/sinks). The “ithink” software (HPS, 1996) represents them with the symbols shown in Figure 2-15. Originally, Forrester used symbols of the DYNAMO (DYNAMIC MODELS) (Forrester, 1971)<sup>3</sup>.

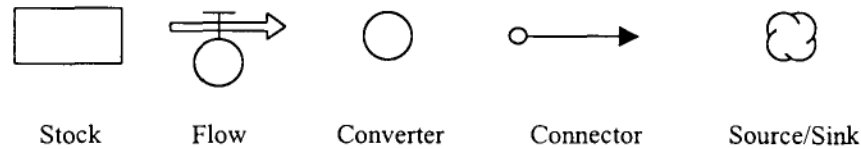


Figure 2-15: Alphabet of the graphical language

**Stocks:** stocks (levels) are accumulators and reflect the conditions or states within a system at any point in time. They persist even when the activity has ceased. A snapshot of a system only would show levels but not flow rates.

**Flows:** flows (rates) are signified by a pipe, with a spigot, flow regulator and arrowhead attached. Thing flows through the pipe in the direction indicated by the arrowhead. The amount of flow is computed by an algebraic expression into the flow regulator, represented by the small circle.

**Converters:** circles represent converters. They are multi input - one output that represent static linear and nonlinear mapping. Converters are used to elaborate the details of the flow rate and level structure in the models. They include functions such as time series, steps, ramps, and pulses, among others.

**Connectors:** connectors reflect the idea “what depends on what”. They represent the relationship among the elements of the system. They do not take on numerical values they just transmit them. This is the difference with Flows.

**Sources and Sinks:** Sources and sinks indicate the boundaries of the model. They are signified by clouds and represent infinite sources; it does not matter what is in the clouds.

<sup>3</sup> DYNAMO was designed by the “Industrial Dynamics Group at Sloan School of Management”, MIT at late 60’s. Currently, the group is named “System Dynamics Group.”

### 2.4.2.2 The Grammar

The foundations of the grammar of the graphical computer language lay on the general expression for the state variable description, which will be present in next section and given by:

$$\dot{x} = f(x, u, t)$$

For the sake of illustration, but without loosing generality, lets assume that the state variable description to be discussed is the particular case of a time-varying linear system.

$$\dot{\mathbf{x}} = \mathbf{A}(t)\mathbf{x}(t) + \mathbf{B}(t)\mathbf{u}(t)$$

$$\mathbf{y}(t) = \mathbf{C}^T(t) + \mathbf{D}(t)\mathbf{u}(t)$$

The grammar rules are then presented as follow:

1. The level variable can only be connected with rate variables.
2. The interaction between two levels can only exist by connecting a rate variable between them.
3. The rate variables are the only ones that interact with level variables.
4. The level variables can only be changed by the effect of rate variables connected to them.
5. Level variables and constants can only affect the rate variables.
6. Even when it is possible to relate rate variables each other, this class of relation is strongly recommended not to use.
7. Initial values (initial conditions) of accumulation are needed to start the simulation.

### 2.4.3 Method

The method starts with the assumption that there is a problematic situation that demands to be understood in order to provide a solution through the change or design of policies.

An analysis using System Dynamics has two objectives<sup>4</sup>:

- To explain the behavior of the system in terms of its structure and policies.
- To suggest changes to structure, policies, or both, seeking an improvement in the problematic situation.

The method consists of 4 stages with a total of 10 steps (Albin, 1997, 6.)

#### Conceptualization

1. Define the purpose of the model
2. Define the model boundary and identify key variables
3. Draw the reference mode of the key variables
4. Diagram the basic mechanism, the feedback loops, of the system.

#### Formulation

5. Characterize the Flows
6. Estimate and select parameter values

#### Testing

7. Test dynamic hypothesis and model assumptions with simulation
8. Test model sensitivity

#### Implementation

9. Analyze policies through the response of the model
10. Translate study insights to an accessible form

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<sup>4</sup> Note that these objectives do not refer at all to the model of the system. Individual models depend on the point of view of the audience. There is no absolutely correct model of a system. All that can be done is to construct the right model of the relevant parts of the system according to a given purpose. So the correctness of the model will depend on the purpose defined by the audience.

1. **Define the model purpose.** The first step in creating a meaningful model from available data and operating knowledge from people familiar with the problem under study is to decide the purpose of the model. It involves making two decisions: (1) on the focus on a problem and (2) on the primary audience of the model. It is important to have in mind that a problematic situation is what is going to be modeled - not a system. If the model can not answer questions of the audience, the model is rendered useless.

In general, the purpose of a model falls into one of the following categories (Albin, 1997, 9:)

- To clarify knowledge and understanding of a situation.
- To discover policies that will improve the situation under study
- To capture mental models and serve as a communication instrument

A useful format for the purpose definition is suggested by (Richmond, 1996) as follows: The purpose of this modeling effort is to develop an understanding of how X influences Y and can contribute to the dynamic patterns (growth, oscillation, decay) experienced by many companies – first category.

Then after, specific questions are set, such as (1) “How are the Company’s policies causing the observed behavior pattern” –second category, (2) “What are we doing to make ourselves vulnerable to competitors” –third category, and (3) “How can we reengineer our structure to minimize this vulnerability” –second category (Richmond, 1996).

2. **Define the model boundary and identify the key variables.** Every feedback system has a closed boundary. The modes of behavior of interest are generated by the interaction of the components within the boundary. The model boundary consists of all the components present in the final model. The model boundary is presented in a form of a component list with two columns. One column for endogenous components and the other one for exogenous components. In the list, Stocks and Flows are also identified to facilitate the last step of the Conceptualization stage, which is Diagram the basic mechanism.

A component is endogenous when it is a dynamic variable involved in a feedback loop. A component is exogenous when its values does not depend directly of the system behavior.

It helps to have in mind the following guidelines to select the components (Albin, 1997):

- (1) they must satisfy necessary conditions to generate and properly represent the

behavior; (2) they should be aggregated, and (3) they must be directional (for example, names that can express growth larger or smaller).

To identify the Stocks and Flows, have in mind Stocks are the accumulations and Flows are the changes in Stocks. Also remember, Stocks are the state variables of the model.

3. **Draw the reference modes of behaviors.** Reference modes of behavior are the plots for the key variables that best characterize the phenomenon under study over time. They capture the mental models and historical data on paper, gives clues about the model structure and allows verification before and after the model is built. There are two types of reference modes: (1) based on mental model hypothesis, and (2) based on historical data. When no historical information is available, the former is used. Common hypothesized reference modes are drawn by hand as exponential growth, exponential decay, S-shaped, overshoot and collapse, and damped, sustained and expanding oscillations. The selection of the time horizon is critical in the development of the reference modes. It is essential that the purpose of the model and the time horizon are consistent each other.
4. **Diagram the basic mechanism, the feedback loops, of the system.** The conceptualization ends with the decisions on the basic mechanisms of behavior. The feedback loops are the basic mechanisms of any dynamic system. In the modeling context, they are seen as the basic structure of cause-effect relationships capable of generating the reference modes. The diagram of the basic mechanisms of a system may be thought of as the stories that expose the dynamic hypothesis on how the reference modes are generated.

Two types of diagrams are found in the literature to represent the basic mechanism: (1) stock-and-flow diagrams and (2) causal diagrams. A **stock-and-flow diagram** is the representation of tentative ideas about how things are changing based on accumulations and rates of changes. This representation forces the modeler to think specifically on the nature of the components and their relationships. The symbolic elements and their functions described in section 2.3.2 for the graphic computer language are used.

A **causal diagram** is the representation of tentative ideas about how variables are correlated using digraphs (nodes and directed arcs). A positive or negative correlation between two variables assigns a "+" or "-" over the arc, respectively. When sequences of arcs start and end at the same point, it is said to have a feedback loop or just a loop. The

polarity of a loop is then assigned as positive or negative depending on the number of minus signs that contains. If the number is odd then the polarity of the loop is negative, otherwise, is positive. Negative loops characterize stable systems and positive loops characterize unstable systems.

Forrester (Forrester, 2000) suggests to avoid the use of causal diagrams and promotes the use Stock-and-Flow diagrams. He observes causal loops do not identify the levels (state of the system) in consequence do not contain measures of the system condition. Cellier (Cellier, 1991) observes the lack of rigor of the causal diagrams as the major weakness of System Dynamics method as a whole. It has to be mention that initial and current proposal of System Dynamics by Forrester does not consider the use of causal diagrams. However, there is abundant literature using causal diagrams.

5. **Characterize the Flows.** The first step in formulation is deciding on the equations of the rates into the Flow elements. Rate equations are of simple algebraic form. They are only functions of constants and values of the level variables. They do not involve nor time, neither solution interval, neither their own past values. It is also strongly recommended that none rate variable depends directly on other rate variable.

Rate equations rule the flows within a system that is controlled. In fact, a rate equation is a policy statement (Forrester, 1971). Policy is a rule that governs decisions. In this context, “policy” and “decisions” cover not only explicit human’s policy and decisions but also those implicit in the system as habits, traditions and natural laws. So, rate equations describe how the available information is used and processed to generate decisions. Rate equations have a subtler representation than level equations. Level equations imply accumulations of something. But, rate equations imply how the decisions of the real system respond to the surrounding conditions. This latter implication involves the particular perception of the people about the real system (their real system).

6. **Estimate and select parameter values.** The last step in formulation is deciding on the parameter values of the model to run on a computer. Exact numerical values are rarely known for all the parameters in the model. They are estimated and selected based on historical data in databases and the mental models of people familiar with the situation under modeling. Both are taken into account with the same weight of importance. Methods for parameter estimation in System Dynamics are discussed in (Richardson and Pugh, 1981), (Graham, 1980), and (Peterson, 1980). Two points to be emphasized: (1) dimension units of parameters must be taken to express consistency among each other



and (2) accuracy of the parameters is based on the aggregate level expressed in the purpose of the model.

7. **Test dynamic hypothesis and model assumptions with simulation.** This step is deciding on the validity of the model. Forrester and Senge are clear about it:

For the public and political leaders, a useful model should explain causes of important problems and providing bases for designing policies that can improve behavior in the future... The notion of validity as equivalent to confidence conflicts with the view many seem to hold which equates validity with absolute truth. We believe confidence is the proper criterion because there can be no proof of the absolute correctness with which a model represents reality. Einstein's theory of relativity has not been proven correct; it stands because it has not been disproved, and because there is shared confidence in its usefulness. Likewise one tests a system dynamics model against diverse evidence, seeks disproof, and develops confidence as the model withstands tests. (Forrester and Senge, 1980, 211).

Randers (Randers, 1980) propose the following questions to be answered in this step. Testing dynamic hypothesis: Do the basic mechanisms actually create the reference mode? Testing model assumptions: Does the model include the important variables? Are the assumed relationships reasonable? Are parameter values plausible?

Validation of a System Dynamics Model is a widely debated point and there is much disagreement on it. Some modelers argue that a model is valid when the model replicates the reference modes. Others like Phillips (Phillips, 1989, 108) consider that requisite decision models are those "... whose form and content are just sufficient to solve a problem." Richardson and Pugh (Richardson and Pugh, 1981, 313) state "The ultimate test of a policy-oriented model would be whether policies implemented in the real system consistently produce the result predicted by the model." Vennix (Vennix, 1998, 89) proposes two premises: (1) "there is not an absolutely valid models," and (2) "Given that we are enable to build perfectly valid models a model's validation can only be judged in the light of its purpose." In this sense, Ljung (Ljung and Glad, 1994) states that the purpose of any model is to answer questions. This research agrees with Ljung and also concludes that the model is valid if the model offers answers and creates confidence.

8. **Test model sensitivity.** This step is deciding on parameters to which the model is sensitive. Sensitive analysis is focused on the amount of change in specific outcomes caused by a determined amount of change in a decision point of the model. Sensitivity analysis is a main concern in the model-building process. One reason is that the problems

commonly tackled by System Dynamics need to incorporate relationships and parameters with few or none empirical data available. This makes difficult the task of quantifying elements of the model. According the definition, a sensitive analysis is “the study of model response to model changes” (Tank-Nielsen, 1980, 187). (Vennix, 1998, 88) proposes the following question to be answered in this step: How sensitive is the model behavior to changes in parameter values? It has two objectives: (1) increasing understanding of the model and (2) locating the sensitive parameter in the model. Three issues are mainly considered in a sensitivity analysis: objectives, types of changes and interpretation of the model response, for a detailed discussion refers to Tank-Nielsen’s discussion. During these analyses, it is observed that Models become insensitive to many parameters within reasonable limits. The reason is the feedback effect. Some changes in parameters can be just seen as disturbances into feedback loops and then the global effect of these changes is completely vanished. However, if the parameters become part of a dominant loop, noticeable changes on behavior will be observed. After locating the sensitive point, three objectives can be established for a research. First, a detailed study on the sensitive parameter. Second, a redefinition of the model to capture the aggregate process expressed by the parameter. Third, if the parameter represents a real factor then attention is pay on this leverage point to improve the policies in which is involved.

Finally, it has to be commented that sensitive analysis are still based on the intuition and judgement of the modeler about the results and perceived outcome. Formal procedures to carry out and evaluate a sensitive analysis can be found in (Tank-Nielsen, 1980), (Wolstenholme, 1990), (Wolstenholme and Al-Alusi, 1987), and (Kleijnen, 1995).

- 9. Analyze policies trough the response of the model.** The first step in implementation is deciding on robust policies represented in the model. Robust policies mean rules relatively insensitive to changes in the model. If policies were sensitive then the results of the model would be largely doubtful of applying in the system. There would not be certain on how policies would work.

Policies are rules that govern decisions. Their corresponding term is “transfer functions” in the field of servomechanism (Forrester, 1994) and “decision rules” in Artificial Intelligence for a knowledge-based system. These rules allow the decision making process by converting information into action.

Testing policies can involve changes: (1) on numerical values in decision points or (2) on the relationships of elements that form the structure of the system. The first one

involves changes in numerical values or in functions employed in a decision point. The second one, on more complex requirements, involves the elimination or addition of relationships to make a decision point more or less informed. Examples and discussions are found in (Vennix, 1998), (Randers, 1980) and (Lynies, 1985).

Since the main reasons to build a System Dynamics model is testing and designing policies that can improve a problematic situation. This happens not only in the simulation model but also in mental models of the participants. Construction of meanings, which are later exposed as changes in behavior of the managers, is one of the bigger results by implementing a System Dynamic model. This result is individual learning in a collaborative environment, one of the most valuable assets in an organization.

- 10. Translate study insights to an accessible form.** The last step in implementation is improving the problematic situation by applying the analysis results. It seems logical that after having studied the problem and obtained robust policies, the next natural step is to implement and register, policies and benefits, respectively. However, the literature reports too many counterexamples on this last step (Vennix, 1998). So, low impact of the model-building process on decision making is observed. It seems the reason is the major development of “modelling by learning” approach using System Dynamics. This approach makes indifferent the notion of implementation after the model results. Since learning is deeply involved in all stages, the problem insights becomes clearer trough the time and slowly solved. At the end of the modeling process the results are obvious and insignificant for the client. In the context of group model-building, the response of the model creates the environment to foster debates and learning about alternative course of actions. Two main products are identified after the model-building process: a written report and learning of the participants.

Two strong recommendations: (1) direct client must be involved and interacting in all the stages instead of the staff and (2) modelers must avoid working in an independent way.

# Chapter 3

## Qualitative Knowledge Acquisition

### Approach

*"... artificial intelligence is the study of computer problems that have not yet been solved. This definition, which Marvin Minsky has been advocating since 1960s, is unlike those found in other fields:"*

(Kurzweil, 1992, 14.)

### 3.1 Knowledge, Modeling, and System Thinking

Knowledge is the growing capacity to respond effectively to a perceived reality to attain a goal (Bourguet and Soto, 2000).

Three parts form knowledge (Chapa, 1973): object, cognitive subject and context. The object is the entity that is desired to be known. The cognitive subject is the entity that approaches to the object in order to know it. The context is the entity that makes meaningful the elements and relationships between the cognitive subject and the object.

Once the elements and the relationships are established between the cognitive subject and the object into a context, the cognitive subject will employ such elements and relationships to respond to a perceived reality. Elements and relationships form policies, which are rules that govern decisions. The better the rules, the better the decisions.

Decisions are actions taken at any particular time as a result from applying policy rules given particular conditions that prevail in that moment. "In System Dynamics models we look upon

managers as information converters to whom information flows and from whom come stream of decisions that control actions within an organization (Simon, 1976, cited by Forrester, 1994, 52).”

Policies are created and improved by a learning process. Learning is the process of constructing meaningful policies. Every cognitive subject has explicit and implicit goals. Meaningful policies are those that allow to attain goals. Training and experiences are part of the learning process.

During learning processes, policies are interrelated forming mental models about reality, so mental models can be constructed. Mental models are those used for understanding the reality and for making decisions. Based on mental models, cognitive subjects would desire to disappear or possess objects. Then cognitive subjects create their concepts and sets of values in this process.

The system of knowledge supports the system of values of a cognitive subject. For example, in a context of business, the perceived value that a customer has of a certain product can be obtained from the system of knowledge that customer possesses. This is one of the reasons why our time is starting to be based on a knowledge economy. The greater amount of information an enterprise has about the knowledge of its clients, the richer the enterprise is.

Managers based on their mental model act as processors that transform information into action. Questions (what, how, when, who, where) are answered with the support of their mental models. Information is then a valuable resource but knowledge, the know-how transforming information into decisions, has become more valuable and difficult for manage it. Currently, Knowledge Management (KM) is the area in charge of this task in business and administration. The search of KM's is addressed toward how to identify intangible assets, to register them in a countable form and to capitalize them in organizations.

Changes are always present, but the rate of change that characterize our time has become so fast that policies in organizations and individual mental models have to change at similar pace if the business has to keep going on. The rhythm of learning has become considered an indispensable competence for a cognitive subject.

The three considered components of knowledge for this research are:

- Context: Modeling for Learning Organization (business and administration.)
- Object: Policies contained in the mental models of managers.
- Cognitive subject: Human participants during knowledge acquisition process via modeling.

As follows, the context of Modeling for Learning Organization is described to give meaning to the proposed approach. In the same sense, System Thinking is then explained to establish the method to perceive the reality and communicate mental models during the interviews for knowledge elicitation.

### 3.1.1 Modeling for Learning Organization

Modeling for Learning Organizations is a “modern” view of modeling that involves the processes of building, using and learning from models. It assumes that models should capture the knowledge and mental data of policymakers, and should blend qualitative mapping with friendly algebra and simulation<sup>5</sup>. The purpose of the models is to support team reasoning and learning. Models have to encourage system thinking and scenarios planning. Simulations provide consistent stories about the future, but not predictions, which have been the traditional use. (Morecroft and Sterman, 1994.)

The concepts of modeling, model and learning organization are established as follows for sake of formality and clarity of this section.

“The process by which a physical system is simplified to obtain a mathematically tractable situation is called modeling. The resulting simplified version of the real system is called the mathematical model, or simply the model of the system.” ... “The word model is derived from Latin and originally means mold or pattern” (Ljung and Glad, 1994, 15)<sup>6</sup>.

The process of modeling as a set of actions for simplifying a reality in an object has different purposes. For science, the main purpose is increase knowledge and generalization. For technology, the main purpose is augmenting prediction capabilities. For art, the main purposes are communication and learning.

Model is a simplified representation of a perceived reality to answer questions. Every model has a client. If the model does not answer significant questions for the client, the model is considered useless.

Learning Organization is “an organization that is continually expanding its capacity to create its future” (Senge, 1990). Learning as the process of construction of “ourselves.”

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<sup>5</sup> Simulation: “The word simulation is derived from Latin *simulare* which means pretends” (Ljung and Glad, 1994.)

<sup>6</sup> Model: “From Latin *modulus* that means small measure. A usually miniature representation of something, also: a pattern of something to be made.” Merriam Webster Dictionary (online dictionary. Digital Library bibdig of ITESM Campus Monterrey, 1999.)

What fundamentally distinguishes a learning organization from traditional “controlling organization” is the mastery of the following five disciplines. Discipline understood as a body of theory and technique putting into practice to acquire certain skills or competencies (Senge, 1990.)

1. System Thinking. It is the discipline based on principles of System Theory that help us to make behavior patterns and structures clearer to understand ourselves as elements of wider systems and to see the effect of our actions through time and space.
2. Personal Mastery. It is the discipline concerning with the continuing clarification and deepness of our personal visions, focus energies, development of patience, and appreciation of reality objectively.
3. Mental models. This discipline refers to working rigorously with our pictures and images that influence how we understand our reality and how we take actions in our world. It also includes the discipline of having “learnful” conversations where people expose their own thinking effectively and allow that this thinking is open to the influence of others.
4. Building Shared Vision. It is the discipline for translating individual vision into a common shared vision. This discipline has inspired organizations for thousands of years and refers to the capacity to hold a shared picture of the future we want to create.
5. Team Learning. This discipline involves a rigorous work with teams as the fundamental learning units in modern organization. If teams can learn then the organization can learn. This discipline helps to develop skills to carry out dialogs where personal assumptions give place to a genuine "thinking together".

Making an analogy between a learning organization and an engineering innovation, the disciplines are for the organization as the technologies are for the engineering innovation. The five disciplines differ from more familiar management disciplines in that they are “personal” disciplines. They have to do with how we think, what we want and what we interact with one another. From this perspective, they are more like artistic than the traditional management disciplines (Senge, 1990.)

From this paragraph to the end of this subsection, the philosophy and antecedents of Modeling for Learning Organizations are paraphrased from (Morecroft and Sterman, 1994.) The concept of Modeling for Learning Organizations was born in 1988 when John D.W. Morecroft of London Business School published in the European Journal of Operational Research a paper called “System Dynamics and Microworlds for Policymakers.” This paper reviewed developments in System Dynamics over the previous ten years and set forth a vision for the

effective use of System Dynamic tools with managers, an approach now known as “modeling for learning.” The approach adopted its formal name in 1992 with the publication of the special issue titled “Modelling for Learning” in the same Journal (vol.59, number 1). Morecroft and Sterman from MIT, currently director of the System Dynamic Group of the Sloan School of Management were the editors.

This modern view positions the role of the model and modeler in a new form:

1. Mental models are “owned” by policymakers, not by technical experts. Models are created in a process that involves a group of policymakers. So the modeling process is carried out collectively and simultaneously with the group. The policy insights from models are disseminated throughout the organization via workshops that are designed to mimic the learning process of the original modeling team.
2. The modelers act as facilitators, as knowledge engineers, who designs and leads group processes to capture team knowledge. The modeler is who designs and delivers learning laboratories, which embed models in an overall learning context of group experimentation and dialogue.

Among the strongest events that influenced the approach are (1) the mini-conference at London Business School on “Computer-Based Learning Environments for Business and Social Systems”, July 1989, and (2) the Learning Conference Series whose meetings took place from May 1987 through October 1989. This latter event had the purpose of exploring the learning of individuals and organizations by diverse analogies to evolutionary learning, biological and ecological adaptation, computer-based learning, and artificial intelligence. The mix included Marvin Minsky and Seymour Papert from MIT’s Media Lab, biologist Peter Warshaw, immunologist Francisco Varela, anthropologist Catherine Bateson, and computer scientist Danny Hillis. The executives included Arie de Geus from Royal Dutch/Shell, Bo Eckman from Volvo, and Jim Pagos from AT&T. The three companies were the sponsors of the series. During the conferences a new vocabulary was generated “Microworlds”, term first coined by Seymour Papert to describe computer-based learning environments. This term fitted uniquely the purpose of business models and simulators that are instruments for strategic change. At the same time, the MIT System Dynamics Group were experimented with “real-time modeling” working with teams of managers and modelers to develop “Management Flight Simulators.” The microworlds embodied a system dynamics model of a particular managerial or strategic issue. The People Express Management Flight Simulator was the first of this kind of microworlds and is currently use in hundreds of institutions for use in education and in corporations.



Two streams of thought have stimulated the role of modeling in organizational learning. On one hand, studies of how people make decisions in complex dynamic environments. On the other hand, studies of interpersonal and groups-process barriers to effective interventions with management teams.

The first stream is conducted by John Sterman and doctoral students using management flight simulators as laboratories at MIT. The results of the experiments showed that people make large, systematic, and persistent errors in environments with modest level of complexity. It was observed that errors arise from what are known as “misperception of feedback” that is the mismatch between the mental models of people and the complexity of the environment. People tend to base on event-level explanations and assume cause and effect closely related in time and space. “I hit him because he took my ball.” However, such linear, short term, open-loop thinking is not quite well adequate to a world that involves multiple feedback and non-linearity: “last month's sales, new budget cuts, who just get promoted or fired” (Senge, 1990). The primary threats to our survival such as pollution, holes of the ozone layer, climate changes come not from close time-space events but from slow gradual processes. According to (Senge, 1990) we are 90 percent blind to these slow processes.

The second stream is conducted by Sterman again, Senge, William Isaac along with Chris Argyris of Harvard, Ed Schein and Donald Schön of MIT and several other thinkers involved in interventions processes and organizational learning. They participated in learning seminars and experimental works to get a deeper appreciation of the role of individual and group process in modeling and learning. Two main challenges are faced: (1) fundamental cognitive limitations on dynamic complexity, and (2) deeply embedded defensive routines, scripts and perceptual filters that prevent from functioning and learning well in teams. It was then stated that tools for modeling and simulation are essential for learning in these settings. However, not only pure technical solutions overcome the damaging open loop thinking prevalent in society today. There exist a mutual necessity of better tools and better process to enhance individual and organizational learning.

### 3.1.2 System Thinking

System Thinking is a form of perceiving a reality based on “seeing” the interrelations among the elements and the process of change of a system. By *interrelations*, it means cause-effect (it should be understood highly correlated and not causal) relationships and by *process of change*, it means processes of balance or reinforce that produce dynamic behaviors.

System Thinking is effective to create understanding of complex situations in, which we are part of, and we are inside. The main benefit of using System Thinking is learning from perceptions of larger windows of time and space than those we have being traditionally trained to use. For example, considering windows of twenty years with a geographic scope of a country provides better elements of understanding than only using city local newspapers of the last semester in order to propose a change in social policies to improve unemployment.

A complex situation is mainly characterized for having a problem in which everybody perceives a problem but nobody knows what the problem is. As a consequence, there is not how to solve it. In a complex situation many perspectives of individuals and groups are involved. Creating communication, consensus and commitment among the parts is the challenging task. The first required process is to develop a collective understanding of the situation. The active participation provides learning in this process.

In decision-making processes, System Thinking allows developing a conscience to balance benefits between:

1. individual and collective issues (social)
2. short and long term issues (time)
3. local and global issues (space)

This conscience allows managing the dynamic complexity in which we are currently participating. Effects of our decisions are not local anymore but global, not only affect current generations but also future generations, and not only our own person or community but also on other communities on whose behavior we depend as well.

On one side, Scientific Method has proven being the most effective approach to create knowledge. Firstly, knowledge and then understanding. However, on the other side, when it is needed to create first understanding and then knowledge, System Thinking has proved to be more effective. The objective of the Scientific method is to create knowledge. It is mainly based on the process of analysis. The objective of the System Thinking is to create understanding. It is mainly based on the process of synthesis. Both Scientific method and System Thinking use analysis and synthesis but in reverse order. Scientific method employs first analysis and then synthesis. System Thinking firstly uses synthesis and then analysis. Both analysis and synthesis were presented in Section 1.2.6.

Given the context, the approach is presented as follows.

### 3.2 Knowledge Acquisition Using System Dynamics

The approach is based on System Dynamics discipline described in Section 2.4 and on the hypothesis that knowledge transmission is carried out by Myths, Symbols and Numbers in every culture (Perez-Morales, 1997-A.) This hypothesis coincides with the operating environment of *Stella II* and *ithink* softwares (Richmond, Peterson, et al, 1993 cited by Peterson, 1994,) one of the most used software in System Dynamics, by having three layers: High-Level Mapping & I/O layer, Model Construction layer, and a mathematical layer.

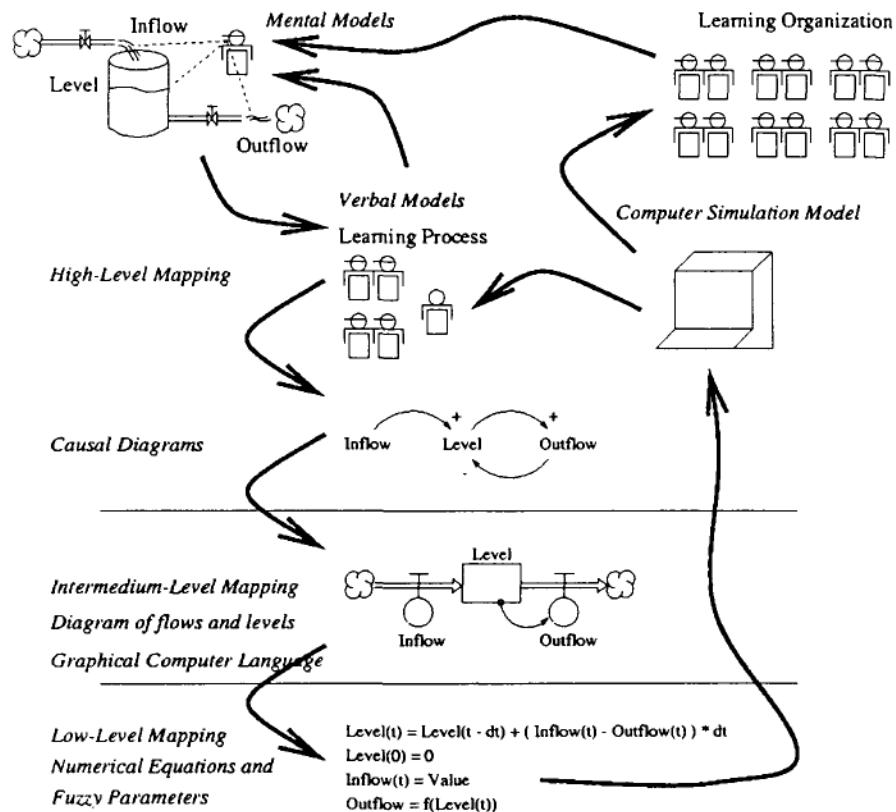


Figure 3-1: Process flow diagram

The proposed approach consists then, by interpreting and synthesizing the ideas expressed above, of three levels of knowledge acquisition, see Figure 3.1: (1) Mapping of high level (Myths) is constituted by mental models, verbal models, and causal diagrams; (2) Mapping of intermediate level (Symbols), by rates of flows and level diagrams, along with a graphical computer language described in Section 2.4.3. (3) Mapping of low level (Numbers) constituted by algebraic and difference equations.

### **3.2.1 Mapping of high level: mental models, verbal models, and causal loop diagrams**

It is characterized by transforming mental models to verbal models and then to causal diagrams. *Mental models* are those that are based on intuition and experience “in the back of our heads” (Ljung & Glad, 1994). Developing these models helps us to learn how to drive a car, how to manage a business. Training and experience develop our mental models. *Verbal models* are those used to describe the behavior of a system under different conditions in words: “if the inflation rate goes up then the bank rate will rise.” Expert systems are considered instances of formalized verbal models. It is not an easy task to convert a mental model to a verbal model. *Causal diagrams* are important instruments to carry out this task. Cause-effect, causal or influence diagrams are names that are used to mean unfortunately the same thing in the context of System Dynamics. They are hypothetically correlated set of relationships, focusing on the feedback linkages among elements of a system. The causal diagram represents the story of how the things work. The process through time or evolution of the system is verbally expressed and drawn in a paper. This operation facilitates and gives shape to discussions among participants at this stage. Basically, no questionnaires are used to gather information from managers. They are just asked to relate the stories in a manner of cause-effect relations.

At this level, the main point sharpens and narrows the intended use or purpose of the model. Also, it is the first attempt to divide the system into subsystems in an aggregate form. Efforts are focused to determine cause and effect relationships. This level demands the modeler a large amount of understanding of and intuition for the system to be described. Hierarchies of complexity and approximations are determined.

The first step is to represent the central loop. Questions made to gather information on the central process are on what the nature of the process is or how the process actually works. Should not be asked, “What are all the factors that influence the process?”

### **3.2.2 Mapping of intermediate level: flow rate and level diagrams, and graphic computer language**

At the intermediate level mapping, the causal diagrams are transformed into a flow rate and level diagram using a graphical computer language. A rate of flows and level diagram is a computer-graphical description of the state variable representation of the system. The state variable representation allows the study of nonlinear and time varying dynamic systems. Even when there

is no way for obtaining an explicit analytic solution for the equation that is describing the system, a realization can be found and a simulation of the system can be obtained. Then the behavior and the cause-effect relations can be observed and analyzed. This characteristic is an advantage for representing complex systems.

The main challenge at this stage is to determine the state variables of the qualitative system description. Physically, a state variable can be associated with a physical storage element. However, for more abstract representations this is not necessary true and a state variable become purely abstract storage but still storage. A generality of the state variables is that they are always the outputs of integrator blocks. For example, the state variable can be associated with the volume of water in a tank but more practically with its level. Level is an easier variable to observe and measure. Since integration implies accumulation, the accumulation of water in the tank is inferred by the level and in this way is an integrated variable. In a similar manner the rate of change of the state variables is related to the rate of flow of water that comes into the tank. Tanks can be seen as the integrator blocks, levels as the states variables, and rates of flow as the rates of change of the state variables. One big advantage of using this state-space description is that initial values of the levels provide the minimal sufficient statistic information to calculate the future response of the system for a new input without worrying about the past.

### 3.2.3 Mapping of low level: numerical equations

The numerical equations are obtained from the flow rate and level diagram. Algebraic and difference first order equations conform now the description of the system. The participants provide set of algebraic equations for every relation among the elements of the diagram. The formal code of the program is automatically generated by *ithink* software, used in this research.

This stage is the most challenging task for the modeler and consists on identifying the system heuristically. It is carried out using the most of the available information resources.

### 3.3 Decision Making Policies Representation Using Fuzzy Logic

The method for policy representation consists of three steps: (1) elicitation of policies from the decision-makers, (2) codification of the policies in a computer, and (3) utilization of the policies in computational models to respond and generate new questions.

#### 3.3.1 Steps of the Method

Step 1. Elicitation of policies from the decision-makers.

The objective is to explicit the knowledge of a decision-maker in a structure of if-then rules. This knowledge acquisition process transforms the mental models to a verbal model and then to a rule-based system model. This kind of models is widely used in Artificial Intelligence by expert systems, which are considered instances of formalized verbal models. The fuzzy rule system constructed in Step 2 can be classified a dedicated small expert system.

Step 2. Codification of the policies in a computer.

The objective is to make the computer comes up with a single conclusion based on the acquired knowledge of Step 1. Mamdani's fuzzy model provides the mechanism of inference to solve the conflict when several rules contribute at the same time. This step should be transparent to the participants since there is no aggregated value for their learning process. In a difference with the traditional method of System Dynamics in which learning is given during the modeling process, at this step there is no learning since only operation min-max are used to articulate the if-then rules.

Step 3. Utilization of the policies in computational models to respond and generate new questions.

The objective is to provide an environment to reflect periodically on the decisions that the computer is making based on the previous Steps 1 and 2. For example, every month during one-year simulation time, the computer generates a change in price as a decision for the current environment information. There is a pause in the simulation in which the participants are asked why the virtual decision maker came up with such a change. Many times the participants are impressed and other intrigued about the performance of their own rules executed by an external entity as the computer. Of course, the performance of

the rules, as isolated object, is different when all the rules work as a whole. As well, different decisions among participants and the computer are often observed. These differences provoke deep reflections and higher conscious about the particular process under management. So, it provides learning.

### 3.3.2 Strategy of Step 1: Elicitation of Policies from the Decision-Makers

1. Select the set of conditions or variables that will be managed.
2. Select the set of goal values for such conditions.
3. Select the variables that will allow decisions to be implemented.
4. Sketch a hypothetical oscillating-damped time response of the deviation for each managed variable.
5. Make clear the meaning of the variables: *deviation* and *Tendency of deviation*.
6. Select two or three, at most, linguistic values (adjectives) for *deviation* and *tendency deviation* with regard to the managed variables.
7. Select two or three singletons, at most, as linguistic values for the driving variables.
8. Represent the knowledge of the manager as a policy system using if-then rules and linguistic values.

#### Details:

1. Select the set of conditions or variables you want to manage. For example, number of customers and profits. The information of these managed variables must be accessible in reality as well as the model.
2. Select the set of goal values for such conditions. These desired conditions are the objectives over all the management exercise.
3. Select the variables that will allow decisions be implemented. These are the variables that will drive the managed variables.
4. Sketch a hypothetical curve of the deviation time response for each managed variable as it is shown in Figure 3-2 (b).

The reason of proposing this qualitative oscillating desired response is based on three requirements. One is to have a representative number of different situations to make

decisions. Two is to have a stable system maintained by policies into negative feedback loops. Finally, three is to have a system capable to reach the goal under the decisions already made. It is known that a system modeled with oscillation will be able to represent systems without oscillations, but not reverse. Also, it should be clear that it is not used as a reference model. It is as tool to elicit decision rules with a qualitative general behavior. Neither overshoot values, nor damped natural frequencies are fixed.

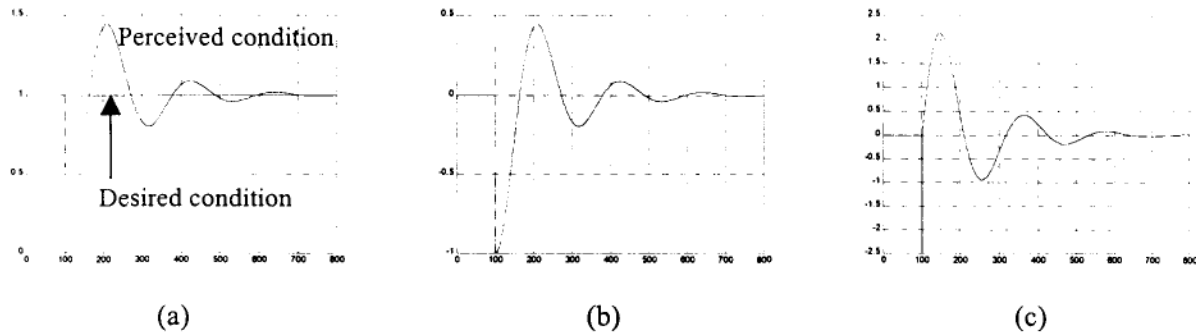


Figure 3-2: Time responses of (a) hypothetical managed variable; (b) deviation of the perceived with regard to desired condition, and (c) tendency of the deviation

5. Make clear the meaning of the variables: *Deviation* and *Tendency of deviation*. A key factor is the understanding of the two variables: (i) deviation ( $e$ ) and (ii) *Tendency of deviation* ( $\dot{e}$ ) with the previous sketched response, see Figures 3.2 (b) and (c), respectively. They indicate how far the current and desired condition are each other and the direction over this gap is moving on. The two variables are necessary for any decision making process. The relevant observation is that the sign (+) or (-) of both *Deviation* and *Tendency of deviation* can be derived from time response sketch of the managed variable. *Deviation and Tendency of deviation* are used as the linguistic variables for the fuzzy rule-based system. Their mathematical expression are shown as follows:

$$e = \text{perceived condition} - \text{desired condition}$$

$$\dot{e} = d e(t)/dt$$

The information contained by these two variables is rich. Every point with not zero value on *deviation* and *tendency deviation* is a condition to be corrected. The ideal condition is when both *Deviation* and *Tendency deviation* are equal to zero. Note that zero deviation can have positive or negative tendency. *Tendency* offers information about the inertia of the system. The policy representation method is based on these two variables.



6. Select two or three, at most, fuzzy sets for deviation and tendency deviation variables. The use of three fuzzy sets is showed in Figures 3.3 and 3.4. Since Multi Inputs - Multi Outputs processes are going to be managed, there are two main reasons for this limited number of fuzzy sets. First reason: it is attempted to cover the complete state space of decisions. This is important because it helps to create confidence in managers. Second reason: it is attempted to avoid the combinatorial explosion problem. For example, by having a process with two inputs, this implies to have two deviations and two tendency deviations, which in turns it is traduced in four linguistic variables. If two fuzzy sets were defined for each linguistic variable, then the total state space of decisions would be  $2^4=16$  decision rules. If three fuzzy sets were used, then  $3^4=81$  decision rules would be needed to cover the complete state space. Now if four fuzzy sets were used, then  $4^4=256$  decision rules would be required, which it turns out to be not practical into a managerial context in order to elicit qualitative knowledge.

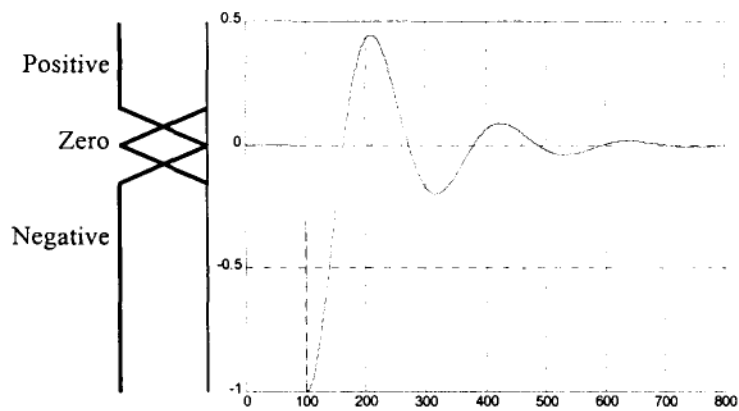


Figure 3-3: Three fuzzy sets cover the range of values for the *deviation* variable

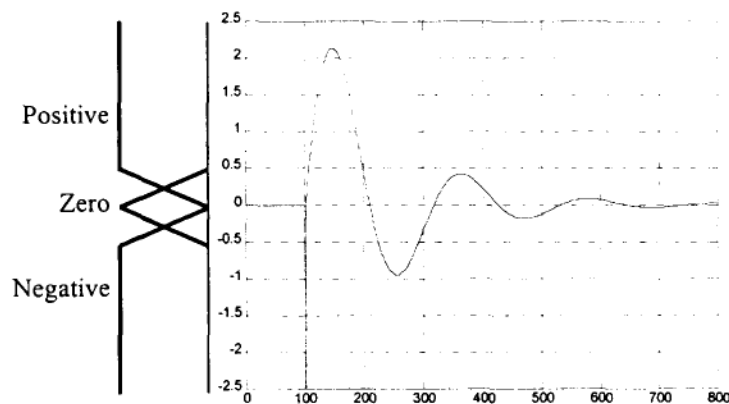


Figure 3-4: Three fuzzy sets cover the range of values for the *Tendency of deviation* variable

7. Select two or three singletons, at most, as linguistic values for the driving variables.

Singletons are the output fuzzy sets they are indeed landmarks in this case. They represent the intensity or the strength of the corrective actions. For example, if *Increment of price* (driving variable) is the linguistic variable then linguistic values can be *Negative* (price decrement), *Zero* (no change), and *Positive* (price increment). How big or small a positive change can be, that is established for the participants and adjusted by the modeler. In Figure 3-5, a set of three singletons is showed behind a graphic of the changes in prices trough the time in order to illustrate what singleton means.

The use of singletons instead of conventional fuzzy sets makes very simple the defuzzification operation. Indeed, this operation will be a weighting sum.

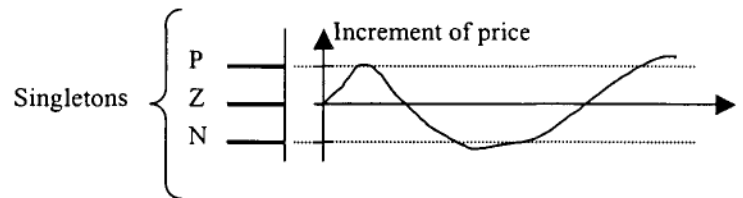


Figure 3-5: Singletons are selected to be the fuzzy sets for the decisions

8. Represent the knowledge of the manager as policies using if-then rules. Use the sketched response and the linguistic values.

For example, ask the question about profits: What kind of action (*Negative*, *Zero* or *Positive*) would you do about the *Increment of price* if the profit *Deviation* is *Zero* and its *Tendency of deviation* is *Negative*? -- condition (point) number 6 in Figure 3-6.

Assume the answer is a *Positive Increment of price*. So, the if-then rule is represented as:

If (*Deviation* is *Zero*) and (*Tendency of deviation* is *Negative*) Then (*Increment of price* is *Positive*)

In other form:

$$\text{If } (e \text{ is } Z) \text{ and } (\dot{e} \text{ is } N) \text{ Then } (\Delta p \text{ is } P)$$

where *Z* (*Zero*), *N* (*Negative*) and *P* (*Positive*) are the linguistic values (also named fuzzy sets) for the linguistic variables *Deviation* (*e*), *Tendency of deviation* ( $\dot{e}$ ), and *Increment of Price* ( $\Delta p$ ).

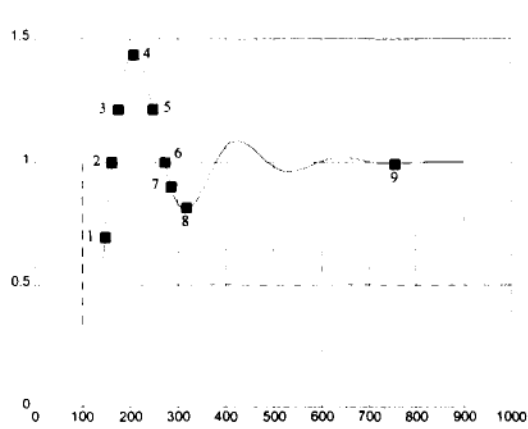


Figure 3-6: Decisions points on the transient response of the Deviation ( $e$ )

Points	If-then rules
1	If ( $e$ is $N$ ) and ( $\dot{e}$ is $P$ ) then ( $\Delta p$ is $Z$ )
2	If ( $e$ is $Z$ ) and ( $\dot{e}$ is $P$ ) then ( $\Delta p$ is $N$ )
3	If ( $e$ is $P$ ) and ( $\dot{e}$ is $P$ ) then ( $\Delta p$ is $N$ )
4	If ( $e$ is $P$ ) and ( $\dot{e}$ is $Z$ ) then ( $\Delta p$ is $N$ )
5	If ( $e$ is $P$ ) and ( $\dot{e}$ is $N$ ) then ( $\Delta p$ is $Z$ )
6	If ( $e$ is $Z$ ) and ( $\dot{e}$ is $N$ ) then ( $\Delta p$ is $P$ )
7	If ( $e$ is $N$ ) and ( $\dot{e}$ is $N$ ) then ( $\Delta p$ is $P$ )
8	If ( $e$ is $N$ ) and ( $\dot{e}$ is $Z$ ) then ( $\Delta p$ is $P$ )
9	If ( $e$ is $Z$ ) and ( $\dot{e}$ is $Z$ ) then ( $\Delta p$ is $Z$ )

A complete set of possible rules for this case is finite and is shown below. The variables are identified as:

Variable to be managed: Profits.

Driving variable: Price.

Linguistic variables: *Deviation*, *Tendency of deviation*, and *Increment of price*.

Linguistic values: *Negative*, *Zero*, and *Positive*.

So:

1. If (*Deviation* is *Negative*) and (*Tendency of deviation* is *Positive*) Then (*Increment of price* is *Zero*)
2. If (*Deviation* is *Zero*) and (*Tendency of deviation* is *Positive*) Then (*Increment of price* is *Negative*)
3. If (*Deviation* is *Positive*) and (*Tendency of deviation* is *Positive*) Then (*Increment of price* is *Negative*)
4. If (*Deviation* is *Positive*) and (*Tendency of deviation* is *Zero*) Then (*Increment of price* is *Negative*)
5. If (*Deviation* is *Positive*) and (*Tendency of deviation* is *Negative*) Then (*Increment of price* is *Zero*)
6. If (*Deviation* is *Zero*) and (*Tendency of deviation* is *Negative*) Then (*Increment of price* is *Positive*)
7. If (*Deviation* is *Negative*) and (*Tendency of deviation* is *Negative*) Then (*Increment of price* is *Positive*)
8. If (*Deviation* is *Negative*) and (*Tendency of deviation* is *Zero*) Then (*Increment of price* is *Positive*)
9. If (*Deviation* is *Zero*) and (*Tendency of deviation* is *Zero*) Then (*Increment of price* is *Zero*)

Or in a matrix form:

$\bullet$ <i>ele</i>	<i>N</i>	<i>Z</i>	<i>P</i>
<i>N</i>	<i>P</i>	<i>P</i>	<i>Z</i>
<i>Z</i>	<i>P</i>	<i>Z</i>	<i>N</i>
<i>P</i>	<i>Z</i>	<i>N</i>	<i>N</i>

In the if-then structure, antecedents are the information about the perceived conditions and the consequent is the decision to be implemented. So this rule system carries out the transformation of information into action, they represent then the policies. An example of an if-then rule is:

If {Deviation on profits} is {Negative} Then {Increment of price} is {Positive}

where the adjectives *Negative* and *Positive* are the values (linguistic values) of the subjects *Deviation on profits* (linguistic variable) and *Increment of price* (linguistic variables).

About the rules that govern such decisions. It seems that they are made by intuition. This process of knowledge acquisition is also a process of reflection for the manager. It is inquired and challenged to explicit his or her tacit knowledge. It seems that even when the decisions are made, there is not always an explicit awareness on their use.

### 3.3.3 Strategy for Step 2: Codification of the policies in a computer

1. Apply the Mamdani's fuzzy model (Mamdani, 1974) to represent the set of obtained policies.
2. Test the policies in the model and adjust parameters.

#### 3.3.3.1 Application of Mamdani's fuzzy model.

It consists of three processes:

- (i) Fuzzification
- (ii) Inference
- (iii) Defuzzification

- (i) **Fuzzification** is the process of classifying a number (crisp value) as a member of several sets and assign it a degree of membership for each set. For example, in Figure 3-7 is shown the linguistic variable *Deviation* ( $e$ ) with its three linguistic values *Negative* (N), *Zero* (Z), and *Positive* (P). A *Deviation* value of  $a/2$  would be classified as member of N, Z, and P fuzzy sets with 0.0, 0.5, and 0.5 degree of membership, respectively. This means, it is not a member of the *Negative* set but it is of the *Zero* and *Positive* sets in a same degree.

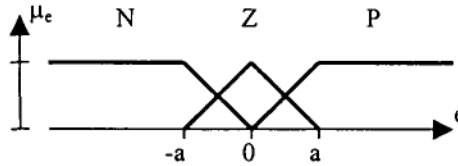


Figure 3-7: Linguistic variable with three values

Every linguistic value has its own fuzzy set and thus its own membership function. Lines 1 and 2 constitute the membership function of the fuzzy set N ( $\mu_e N$ ); lines 3 and 4, the membership function of Z ( $\mu_e Z$ ), and lines 5 and 6, the membership function of P ( $\mu_e P$ ). A *Deviation* value between  $-a$  and  $0$  will belong to the sets N and Z; between  $0$  and  $a$ , to Z and P, and lower than  $-a$  and bigger than  $a$  exclusively to N and P, respectively.

The equations for the three membership functions are described below. Note that  $a$  is the only parameter to be adjusted for this case.

$$\mu_e N = \begin{cases} 1 & ; e < -a \\ -\frac{1}{a}e & ; -a \leq e \leq 0 \\ 0 & ; e > 0 \end{cases} \quad \mu_e Z = \begin{cases} \frac{a+e}{a} & ; -a \leq e \leq 0 \\ \frac{a-e}{a} & ; 0 < e \leq a \end{cases} \quad \mu_e P = \begin{cases} 0 & ; e < 0 \\ \frac{1}{a}e & ; 0 \leq e \leq a \\ 1 & ; e > a \end{cases}$$

The description when two linguistic values are used N and P, which is the case that will be implemented in the following section, follows:

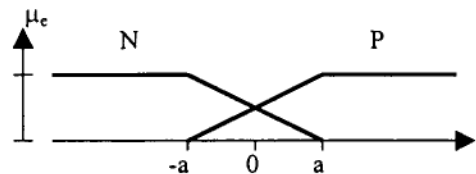


Figure 3-8: Linguistic variable with two values

$$\mu_e N = \begin{cases} 1 & ; e < -a \\ \frac{a-e}{2a} & ; -a \leq e \leq a \\ 0 & ; e > a \end{cases} \quad \mu_e P = \begin{cases} 0 & ; e < -a \\ \frac{a+e}{2a} & ; -a \leq e \leq a \\ 1 & ; e > a \end{cases}$$

- (ii) **Inference** is the process of generating conclusions. One single conclusion is obtained at the end of this process. The Mamdani's fuzzy model uses the Max-Min operations for this purpose. The Min operation is applied to conclude in every individual if-then rule. The Max operation is applied to aggregate the individual fuzzy sets obtained from the conclusions. In this way, conflicts on the conclusions are solved.

The codification of the nine if-then rules gathered in Step 1 is shown below. First, Min operation is applied and then after Max operation. The result of this Step is the conclusion for  $\mu_{\Delta p}N$ ,  $\mu_{\Delta p}Z$  and  $\mu_{\Delta p}P$ . The next process will convert this fuzzy variable into a crisp number.

- 1 If ( $e$  is  $N$ ) and ( $\dot{e}$  is  $P$ ) Then ( $\Delta p$  is  $Z$ )  $\mu_{\Delta p}Z_1 = \text{Min}(\mu_e N, \mu_{\dot{e} P})$
- 2 If ( $e$  is  $Z$ ) and ( $\dot{e}$  is  $P$ ) Then ( $\Delta p$  is  $N$ )  $\mu_{\Delta p}N_2 = \text{Min}(\mu_e Z, \mu_{\dot{e} P})$
- 3 If ( $e$  is  $P$ ) and ( $\dot{e}$  is  $P$ ) Then ( $\Delta p$  is  $N$ )  $\mu_{\Delta p}N_3 = \text{Min}(\mu_e P, \mu_{\dot{e} P})$
- 4 If ( $e$  is  $P$ ) and ( $\dot{e}$  is  $Z$ ) Then ( $\Delta p$  is  $N$ )  $\mu_{\Delta p}N_4 = \text{Min}(\mu_e P, \mu_{\dot{e} Z})$
- 5 If ( $e$  is  $P$ ) and ( $\dot{e}$  is  $N$ ) Then ( $\Delta p$  is  $Z$ )  $\mu_{\Delta p}Z_5 = \text{Min}(\mu_e P, \mu_{\dot{e} N})$
- 6 If ( $e$  is  $Z$ ) and ( $\dot{e}$  is  $N$ ) Then ( $\Delta p$  is  $P$ )  $\mu_{\Delta p}P_6 = \text{Min}(\mu_e Z, \mu_{\dot{e} N})$
- 7 If ( $e$  is  $N$ ) and ( $\dot{e}$  is  $N$ ) Then ( $\Delta p$  is  $P$ )  $\mu_{\Delta p}P_7 = \text{Min}(\mu_e N, \mu_{\dot{e} N})$
- 8 If ( $e$  is  $N$ ) and ( $\dot{e}$  is  $Z$ ) Then ( $\Delta p$  is  $P$ )  $\mu_{\Delta p}P_8 = \text{Min}(\mu_e N, \mu_{\dot{e} Z})$
- 9 If ( $e$  is  $Z$ ) and ( $\dot{e}$  is  $Z$ ) Then ( $\Delta p$  is  $Z$ )  $\mu_{\Delta p}Z_9 = \text{Min}(\mu_e Z, \mu_{\dot{e} Z})$

$$\mu_{\Delta p \text{Negative}} = \text{Max}(\mu_{\Delta p}N_2, \mu_{\Delta p}N_3, \mu_{\Delta p}N_4)$$

$$\mu_{\Delta p \text{Zero}} = \text{Max}(\mu_{\Delta p}Z_1, \mu_{\Delta p}Z_5, \mu_{\Delta p}Z_9)$$

$$\mu_{\Delta p \text{Positive}} = \text{Max}(\mu_{\Delta p}P_6, \mu_{\Delta p}P_7, \mu_{\Delta p}P_8)$$

- (iii) **Defuzzification** is the process of deriving a crisp number from its corresponding fuzzy set membership degree. A final conclusion given in a form of a fuzzy variable is the result of the inference process. The Defuzzification process transforms this fuzzy variable into a crisp value, a number, which will be the decision of the virtual decision-maker.

Based still on Mamdani's fuzzy model and using singletons as the output fuzzy sets, the Defuzzification process is simply a weighting sum. For the example of the increment of price:

$$\Delta p = \frac{\mu_{\Delta p \text{Negative}} * SN + \mu_{\Delta p \text{Zero}} * SZ + \mu_{\Delta p \text{Positive}} * SP}{\mu_{\Delta p \text{Negative}} + \mu_{\Delta p \text{Zero}} + \mu_{\Delta p \text{Positive}}}$$

where SN, SZ, and SP are the output fuzzy sets or singletons.

### 3.3.3.2 Test the policies in the model and adjust parameters

The parameters required to be adjusted are  $a$  in every linguistic variable and the output singletons. For the example presented in this section, they are 5 parameters.

Linguistic variables	Parameters to be adjusted
<i>Deviation</i>	$a$
<i>Tendency deviation</i>	$a$
<i>Increment of price</i>	$N, Z, P$ (singletons)

The participants suggest initial values for all of them. The modeler will adjust them later without the intervention of the participants. This adjustment is carried out by trial and error until a satisfactory performance is obtained, according the modeler.

Two rules of thumb are recommended to have in mind:

- The bigger the  $a$ , the softer the corrective action of the decision.
- The farther the  $N$  and  $P$  from zero, the harder the corrective action of the decision.

For initial value of  $a$ , the acceptable limit superior or inferior of a deviation with respect the goal can be considered as a good value, same for a tendency deviation. Initial values of the singletons  $N$ ,  $Z$ , and  $P$  are suggested to be zero for  $Z$ , and an average change value of a corrective action during the time to be observed for  $N$  and  $P$  in a symmetric way around zero.

### **3.3.4 Strategy for Step 3: utilization of policies in computational models to respond and generate new questions**

1. Challenge the participants to drive the business in the computer.
2. Ask the participants for observing how the virtual decision-maker performs in the same task. Allow them to periodically discuss the events enabling pauses during the simulation.
3. Compare the performance of the participants and the virtual decision-maker. Emphasize the fact that he or she is competing against his or her own knowledge.
4. Adjust policies in the knowledge-based fuzzy system.
5. Let the participants execute as many times as they desire Step 3 in order to allow them to adjust their own policies through active discussions. The focus of Step 3 is to facilitate learning among the participants, making reflections of their own actions.

Application results are presented in the following chapter.

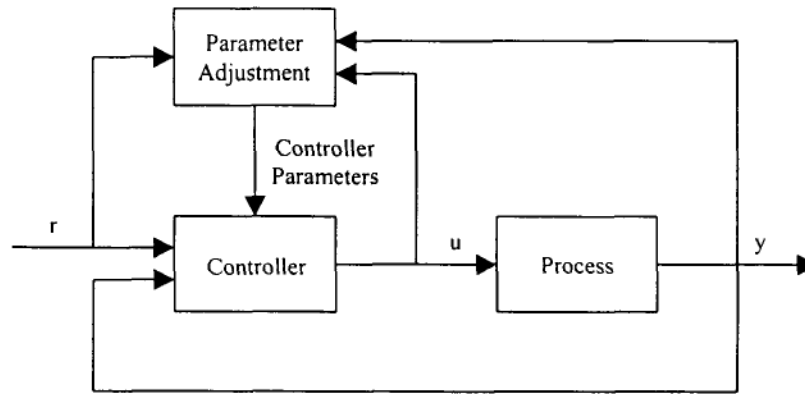
## **3.4 Adaptive Mechanism**

"an adaptive controller is a controller with adjustable parameters and a mechanism for adjusting the parameters." (Åström and Wittenmark, 1995, 1). This was the pragmatic attitude that was taken by referenced authors, worldwide authorities, in their book after briefly reviewing some attempts to define adaptive control since 1961 in symposiums and IEEE committees.

In intelligent systems, an adaptive mechanism follows the same principle. Set of parameters that has to be adjusted by a mechanism to change the behavior of the system in order to face new circumstances. This adaptation mechanism can then be used also as an automatic tuning mechanism of parameters. This usage has been taken in the present work.

The general structure of this kind of systems is comprised by two loops. An inner loop, which is in charge of the task achievement of the system, and an outer loop, in charge of the inner loop performance. The outer loop adjusts the parameters of the control strategy mechanism. The structure is shown in Figure 3-9 (adapted from Åström and Wittenmark, 1995, 2).

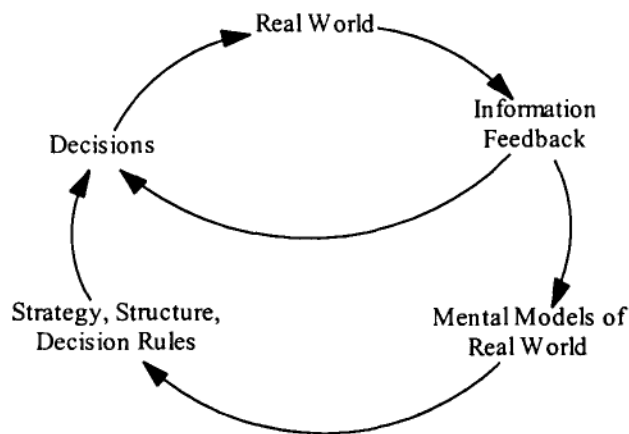




**Figure 3-9: General structure of an adaptive system**

The parameters to be adjusted are contained in the control strategy block labeled as "Controller." The block of the adaptation mechanism labeled as "Parameter Adjustment" transforms the information of the signals reference ( $r$ ), control action ( $u$ ), and output ( $y$ ) of the system labeled as "Process" in updated parameters of the Controller.

This double-loop structure was also discovered and described by (Argyris, 1985 cited by Sterman, 1994) in a context of human organizations. Indeed, it was called the Double-Loop Learning, see Figure 3-10. Here the information of the Real World is used in the inner loop to make decisions, that in turn these decisions will alter the Real World. It is the analogous inner loop of the general structure of an adaptive system. Argyris and Sterman argue that there is not learning at the inner loop, just reactive actions to reach specific goals. The learning is produced at the outer loop when information alters the mental models. Mental models contain the strategies, structures and decision rules that allow people map information into action during the decision making process.



**Figure 3-10: Double-Loop Learning by Argyris (1985 cited by Sterman 1994)**

"The development of Systems Thinking is a double-loop learning process in which we replace reductionist, partial, narrow, short term view of the world with a holistic, broad, long-term, dynamic view and then redesign our policies and institutions accordingly. Such learning involves new articulations of our understanding, or reframing of a situation, and leads to new goals and new decision rules, not just new decisions" (Sterman, 1994, 297.)

Since the double loop structure appears in the context of human organizations for learning and in the context of intelligent machines for adaptation, a brief description of the three main adaptive schemes in control theory are described in order to generate a better understanding of human learning. The adaptive algorithm implemented in the program is shown in Chapter 4. It is based on the MIT rule described at the end of this chapter. The algorithm allows adjusting the decision rules of the machine by adjusting the singleton values.

### 3.4.1 Adaptive Schemes

Three main adaptive schemes are found in adaptive control applications (Wittenmark, 1997, 33-34), (Åström and Wittenmark, 1995, 19-22):

1. Gain Scheduling
2. Model-Reference Adaptive Systems (MRAS)
3. Self-Tuning Regulators (STR)

Gain Scheduling and MRAS are referred to as direct methods and STR as indirect method. The difference is the formers use adjustment rules that directly assign the controller parameters. The latter, firstly estimate the parameter of the process model and then using the solution for a design problem, implemented in a function, assign the controller parameters.

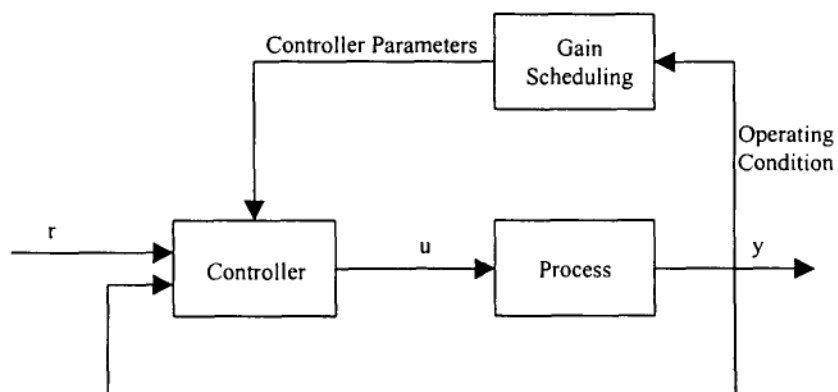


Figure 3-11: Block diagram of a system with gain scheduling

### 3.4.1.1 Gain Schedule

A block diagram of a system with Gain Scheduling is shown in Figure 3-11. The system has two loops. They are the normal feedback inner loop and the adjusting outer loop.

Gain scheduling is the simplest of the three schemes. It and can be considered as a mapping function from process parameters to controller parameters based on current operating conditions. It can be implemented as a function or a table lookup (Åström and Wittenmark, 1995, 19-20).

### 3.4.1.2 Model-Reference Adaptive Systems (MRAS)

A block diagram of a system with MRAS is shown in Figure 3-12. The system presents two loops. An ordinary feedback inner loop and an adjusting outer loop (Åström and Wittenmark, 1995, 20-21). The outer loop adjusts the controller parameters based on a policy that drives the difference between process output  $y$  and the model output  $ym$  to a small value.

The purpose of this scheme is to solve the problem in which the performance specifications are given in terms of a reference model.

One of the challenges with MRAS is to guarantee stability of the system by selecting an adequate adjusting mechanism.

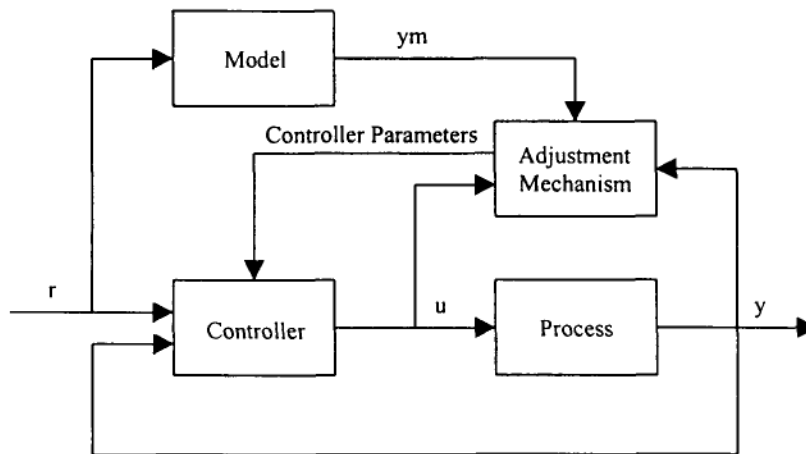


Figure 3-12: Block diagram of a system with MRAS structure

The MIT rule was originally used as adjusting policy, this is:

$$\frac{d\theta_s}{dt} = -\gamma e \frac{\partial e}{\partial \theta}$$

where  $e = y - y_m$ ,  $\theta$  is a controller parameter,  $\gamma$  is the adaptation rate, and  $\frac{\partial e}{\partial \theta}$  indicates the sensitivity of the error with regard the  $\theta$  parameter. This rule can be considered as a gradient scheme to minimize the squared error  $e^2$ .

The MIT rule is used in this research with satisfactory results and it will be explained with more detail in Section 3.4.2.

### 3.4.1.3 Self-Tuning Regulators (STR)

A block diagram of a system with STR is shown in Figure 3-13. The system contains the two loops mentioned above. The process and an ordinary feedback controller comprise the inner loop. A recursive parameter estimator and a design calculation mechanism, which adjust the controller parameters, comprise the outer loop (Åström and Wittenmark, 1995, 21-22).

This scheme can be viewed as an automation of the process of modeling and design where an update is carried out at each sampling period.

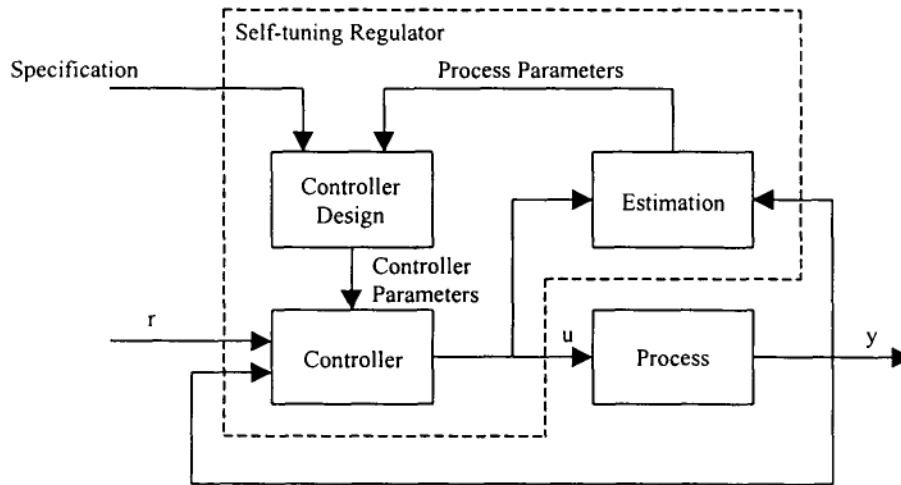


Figure 3-13: Block diagram of a system with STR structure

## 3.4.2 The MIT Rule

The MIT Rule was originally proposed for systems with MRAS scheme (Åström and Wittenmark, 1995, 186-187). It was developed at the Instrumentation Laboratory (now the Draper Laboratory) at MIT, that is why the name is derived.

For the sake of explanation, let consider the MRAS scheme shown in Figure 3-11 with a controller having just one parameter  $\theta$ . The MIT Rule is designed then to adjust the parameter  $\theta$  to minimize the loss function:

$$J(\theta) = \frac{1}{2}e^2$$

where  $e = y - y_m$ ,  $y$  is the output of the process to be controlled and  $y_m$  is the output of the process model.

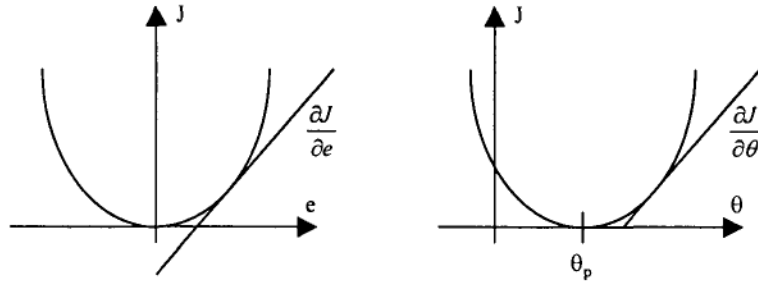


Figure 3-14: Gradients of  $J$  with respect to the error and the controller parameter  $\theta$

One reasonable possibility is to change  $\theta$  in the direction of the negative gradient of  $J$ , this is-- see Figure 3-13 for geometrically interpretation in which  $\theta_p$  appears as real  $\theta$  of the process:

$$\begin{aligned} \frac{d\theta}{dt} &\propto -\frac{\partial J}{\partial \theta} \\ \frac{d\theta}{dt} &= -\gamma \frac{\partial J}{\partial \theta} \end{aligned}$$

since:

$$\frac{\partial J}{\partial \theta} = e \frac{\partial e}{\partial \theta}$$

The MIT Rule is:

$$\frac{d\theta}{dt} = -\gamma e \frac{\partial e}{\partial \theta}$$

where  $\frac{\partial e}{\partial \theta}$  is called the *sensitivity derivative* of the system. It tells how much  $\theta$  influence the error. The scheme is derived in such a way that parameter changes are slower than other variables in the system. Then  $\frac{\partial e}{\partial \theta}$  can be evaluated under the assumption that  $\theta$  is constant.

Another alternative for the loss function is:

$$J(\theta) = |e|$$

then following the gradient method, it gives:

$$\frac{d\theta}{dt} = -\gamma \frac{\partial e}{\partial \theta} \text{sign}(e)$$

The first MRAS used this adjusting rule.

The variable  $\theta$  and  $\partial e / \partial \theta$  should be interpreted as the controller parameter vector and the gradient vector of the error with respect to the set of parameters, respectively, when the controller has more than one parameter (Åström and Wittenmark, 1995, 187).



## Chapter 4

# Application and Simulation Results

*“ ... Once you learned how to ask questions – relevant and appropriate and substantial questions – you have learned how to learn and no one can keep you from learning whatever you want or need to know.”*

(Neil Postman and Charles Weingartner cited by Christensen, 1991, 157.)

The objective of the chapter is to show the results of jointly using System Dynamics and Fuzzy Logic to acquire qualitative knowledge about dynamics of a complex system<sup>7</sup>. Specifically, a problematic situation of a hotel business and a set of policies for its administration are presented.

The objective of the developed tool, which is a program implemented by using *ithink* software, is to create and shape discussions among participants in seminars and workshops to develop general managerial skills. The tool is used neither for forecasting, nor for training managers of hotels. The purpose of the tool falls into the category of capturing mental models and serves as a communication instrument.

---

<sup>7</sup> Complex Systems are characterized by: (1) having conflicts between short and long terms goals; (2) having few leverage points, which are usually not in the obvious places where people think; (3) present properties of self-organization, adaptation and emergent properties. In general, these systems, in comparison with simple systems, are “able to process more information, anticipate changes of the



Case under modeling is presented in Section 4.1. Characteristics of hotel business are described in Section 4.2. Qualitative knowledge acquisition process for the problematic situation by using System Dynamics is presented in Section 4.3. Policies representation by using Fuzzy Logic, in Section 4.4. Implementation of an adaptive mechanism is shown in Section 4.5. Finally, simulation results are presented in Section 4.6.

## 4.1 Case of Study: Hotel Business and Administration

The approach was applied to elicit and represent the knowledge of the dynamic of a five-star hotel by request of a consulting firm.

The objective was to construct a simulator that allowed to shape discussions and to expose skills to make decisions among managers.

The scope is limited to a one-year experimental research in a group with three participants. The business problematic situation to be modeled is characterized by having a low profit scenario. The set of considered policies transform the information of clients and profits to actions in price and service quality offered by the hotel.

A team of three persons was integrated to realize the part of knowledge acquisition:

- a hotel administrator
- a consultant of quality programs and
- a knowledge engineer

### Problematic Situation

A five-star hotel, having several years running well on business is facing now a problematic situation. The profits have declined almost to a level of zero. The main reason is the large lost of clients. The current situation is profits have declined because of the old and potential clients have been taken by the competitors. The decrement of profits has caused a delay in new investment and thus a continuous deterioration of the hotel service quality.

The manager and the owner have to make decisions on *Price* and *Service Quality* every month during one year. If they increase the Service Quality, the Customer Satisfaction will increase, as well as Room Reservations, Occupancy Percentage, and as a consequence Incomes

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environment more accurately, learn more quickly, act more flexibly and are generally able to respond more appropriately to a wider range of changing circumstances" (Kauffman, 1980, 32).

and Profits will increase. However, the cost for increasing Service Quality is faster noted in Profits by decreasing it almost immediately. There exists then a conflict between short and long term benefits. This kind of conflict is a basic characteristic of complex systems.

## 4.2 Business and Management of Hotels

From a business context, hotels are businesses of commercial hospitality, which offers its facilities and services for sale (Medlik and Ingram, 2001, 13.) In most countries, the hotel industry plays an important role in the economies and societies. This industry provides facilities for business transactions, for meeting and conferences, and for recreation and entertainment. Hotels are considered attractions for visitors, foreign currency earners, employers of labor, outlets for the products of other industries, and source of amenities for local residents (Medlik and Ingram, 2001, 4-5.)

The primary function of a hotel is to provide for reward services of accommodation to those people away from home, and to supply them their basic needs, such as food, drinks and sometimes others facilities for travelers and temporary residents (Medlik and Ingram, 2001, 4.)

A hotel can be seen as a business system that transforms costs to revenue, employees to job satisfaction, tired and hungry customers to fed and rested customers, capital to return on investment, time and effort to wages and salaries (Medlik and Ingram, 2001, 171-172.) The success of a hotel depends on how well the hotel performs these transformations.

### 4.2.1 Types of Hotels

Types of hotels are classified by according the following criteria. *Location* by referring to be inland, coastal, mountain.) *Position*, with regard to town-center, suburb. *Related to transport* such as motor, railway, airport. *Purpose of visit*, business, holidays, and convention. *Duration* being in transit or residential. *Facilities or service provided* for instance only overnight accommodation or apartment hotel. *Licensed*, for example for selling alcoholic liquor. *Size*, e. g. a large hotels are those whose number of beds or bedrooms range from one to several hundreds. *Ownership and management*, by distinguishing owned independent hotels from chain or group hotels.

Whatever the criteria is used, there are five grades for classifying the facilities and services provided. Five stars denote the extreme of luxury (quality hotels.) One star denotes the basic standards (economy.) (Medlik and Ingram, 2001, 10-11.)

### **4.2.2 Yield (or Revenue) Management**

Yield (or revenue) management "is the application of information systems and pricing strategies to allocate the right capacity to the right customer at the right place at the right time" (Kimes, 2000, 4.) As a result, allocating undifferentiated units of capacity to available and differentiated demand maximizes profits or revenues. The main idea is then to maximize profit (or revenue) by selling limited low-priced units to price-sensitive customers willing to purchase at off-peak times, and selling high priced units to price-insensitive customers who want to purchase at peak times. The problem is to determine how much to sell at what price and to which market segment.

Hotels and airlines industries have adopted this method for managing their capacities profitably. The term "yield" was originated in the airline industry and it refers to yield (or revenue) per available seat mile. The concept applies to other industries by referring to yield (or revenue) as the available time-based inventory unit.

The basic method of demand and supply for managing a hotel is another option. Pricing is again the driving strategy, but now it depends on the current demand. The higher the demand, the higher the price.

The pricing strategy based on demand and supply was implemented in the simulator as a first approximation. The reason is the current problematic situation of the hotel. It is necessary to decide on the goal customer profile and then investments required to infrastructure.

## **4.3 Qualitative Knowledge Acquisition of a Problematic Situation Using System Dynamics**

The method described in Section 2.4.4 is applied to elicit and represent the problematic situation described above. The four stages of the method are (1) conceptualization, (2) formulation, (3) testing, and (4) implementation.

### **4.3.1 Conceptualization**

#### **Purpose of the model**

The purpose of the model is to represent the problematic situation described about five-start hotel on the conflict of short and long-term benefits in profit by making decisions on the service quality and price offered by the hotel.

The model will be used as an element to create and shape discussions among participants in seminars and workshops to develop general managerial skills.

The model will not be used for forecasting.

The model will not be used for training managers of hotels.

The purpose of this model falls into the category of capturing mental models and serves as a communication instrument.

### **Model Boundaries and Key Variables**

The model boundaries refer to the significant dynamics to be considered. The selection of variables and their interrelation define then the boundaries of the model.

Time horizon: one year.

It has been established to model four type of customer profiles:

Directs	are customers who directly select the hotel from their previous experiences, recommendations, or information given by different media.
Agencies	are customers who take tourist packages offered by travel agencies.
Airlines	are customers who take the options of a package with transportation and hotel in business travels offered by airlines.
Commercials	are customers whose companies have commercial relationships with the hotel in specific seasons of the year.

Key variables:

- Hotel Service Quality
- Customer Quality Profile
- Customer Satisfaction Grade
- Market Total Segment
- Market Segment of the Hotel
- Room Reservations
- Hotel Occupancy Percentage
- Costs per month
- Incomes per month
- Profit per month
- Accumulated Customer Satisfaction
- Customer Profile Cost
- Customer Profile Fare
- Hotel Total Capacity

Table 4-1: Exogenous and endogenous variables

Exogenous	Endogenous
Hotel Service Quality	Market Total Segment
Customer Quality Profile	Market Segment of the Hotel
Customer Satisfaction Grade	Room Reservations (S)
Customer Profile Cost	Hotel Occupancy Percentage
Customer Profile Fare	Costs per month (F)
Hotel Total Capacity	Incomes per month (F)
	Profit per month
	Accumulated Customer Satisfaction (S)

Exogenous and endogenous are identified from the list of key variables and shown in Table 4-1. Stocks (S) and Flows (F) are denoted in the endogenous variables.

### Reference Modes

Reference modes are hypothesis of expected behavior of key variables. Reference mode for *Accumulated Customer Satisfaction* is shown in Figure 4-1. Three key variables are chosen:

- **Accumulated Customer Satisfaction.** It refers to the aggregate customer satisfaction per profile accumulated since the beginning of the year until the current month. Customer satisfaction is understood as the level of match between two issues. One is the match between the quality expected and provided by the customer and the hotel, respectively. Another one is the match between the price expected by the customers and offered by the hotel.
- **Accumulated Incomes.** It refers to accumulated revenue mix of rooms, food, beverages, and rentals until the current month.
- **Accumulated Costs.** It refers to the accumulated variable and fixed costs or charges since the beginning of the year until the current month. Variable costs include departmental cost of sales, departmental payroll and related expanses on rooms, food, and beverages. Also undistributed operating expanses, such as, administration, marketing, property operation, maintenance, energy. Fixed costs include rent and depreciation (Medlik and Ingram, 2001, 139.)

If a specific class of customer is satisfied, more customers of this class will arrive, building a bigger number of satisfied customers. In other words, the class of customer falls in a reinforcing loop. If the reverse occurred then unsatisfied customers of a class will put further away others. This reinforcing process lasts while the limits of growth are not reached.

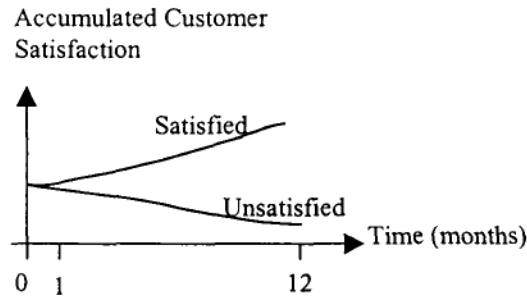


Figure 4-1: Reference Mode for Accumulated Customer Satisfaction

Three scenarios are proposed in Figure 4-2 for accumulated incomes and costs in order to compute profits. Figure 4-2 (a) shows the current state of the hotel. If no change is made the hotel will remain almost in balance. So doing nothing is always a possible option.

Figure 4-2 (b) shows a scenario where fast and short-term benefits are looked forward. Decreasing Service Quality decreases cost reduction. At the beginning, profits are increased however after a long period of time the hotel will have fewer customers because of unsatisfied service and as consequence less incomes.

Figure 4-2 (c) shows a scenario looking for long-term benefits. Profits are punished during the first part of the year. However at the end of the year, profits and its tendency are favorably sustained. Even though, this scenario seems favorable, not all the business can support such punishment to the profits.

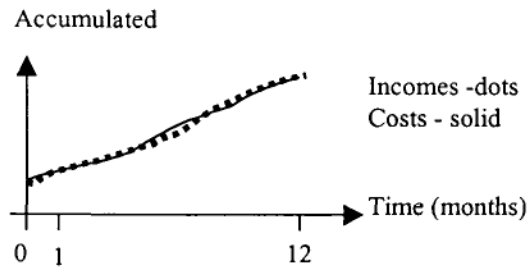
The reference modes will be the guides during the modeling effort.

### Basic Mechanism

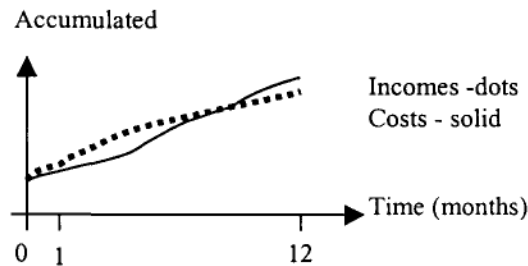
The basic mechanisms are shown in Figure 4-3 in the form of a **causal diagram**. In the diagram, letters **S** and **O** indicate positive and negative correlation between related variables.

The causal diagram relates the following story. Numbers on the relationships are shown in Figure 4-3 (b) to make easier the narration. First assuming positive Customer Satisfaction and the reinforcing loop R1: (1) the larger the number of Room Reservations, the bigger the Occupancy Percentage; (2) the bigger the Occupancy Percentage, the larger the number of Room

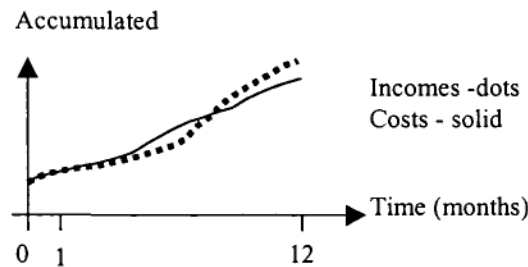
Reservations. This loop finds its limits to growth when the capacity of the hotel is reached. Now assuming a negative Customer Satisfaction, from (1) the smaller the number of Room Reservations, the less Occupancy Percentage; from (2) the less the Occupancy Percentage the smaller the number of Room Reservations. The loop finds its limits to diminution when there is not more customers.



(a)



(b)



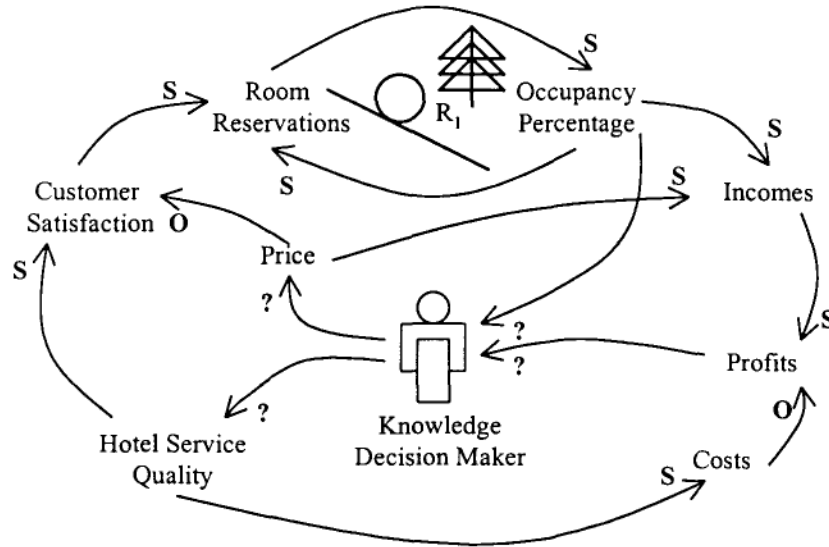
(c)

**Figure 4-2: Reference modes for Accumulated Incomes and Costs: (a) in balance, (b) with short-term benefits, and (c) with long-term benefits**

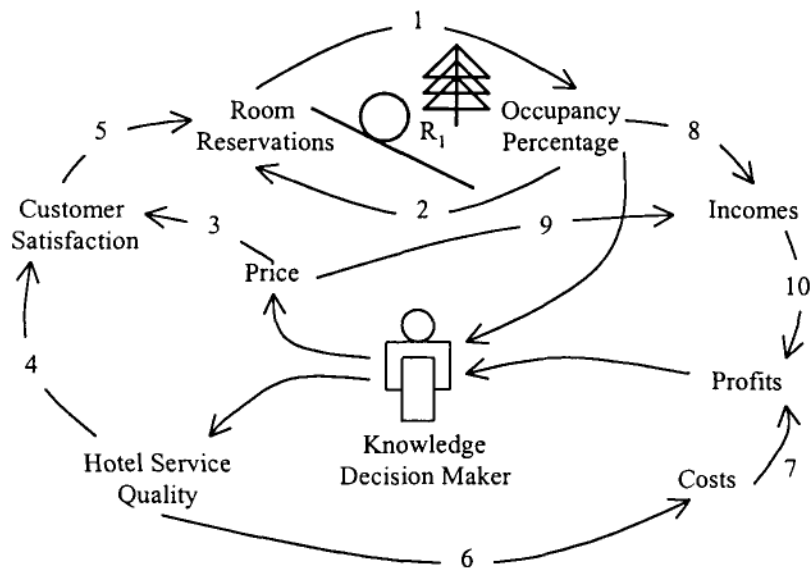
Following the left branches, (3) the higher the Price, the lower the Customer Satisfaction; (4) the better the Hotel Service Quality, the higher the Customer Satisfaction; (5) the higher the Customer Satisfaction, the larger the number of Room Reservations. On the bottom branch, (6) the higher the Hotel Service Quality, the higher the Costs; (7) the higher the Costs, the lower the

Profits. On the right branch, (8) the bigger the Occupancy Percentage, the higher the Incomes; (9) the higher the Price, the higher the Incomes; (10) the higher the Incomes, the higher the Profits.

This story agrees with (Haskett, 1992, cited by Ingram, 1996, 30) about the self-reinforcing cycle that is comprised by quality, repeat usage, profits, and investment.



(a)



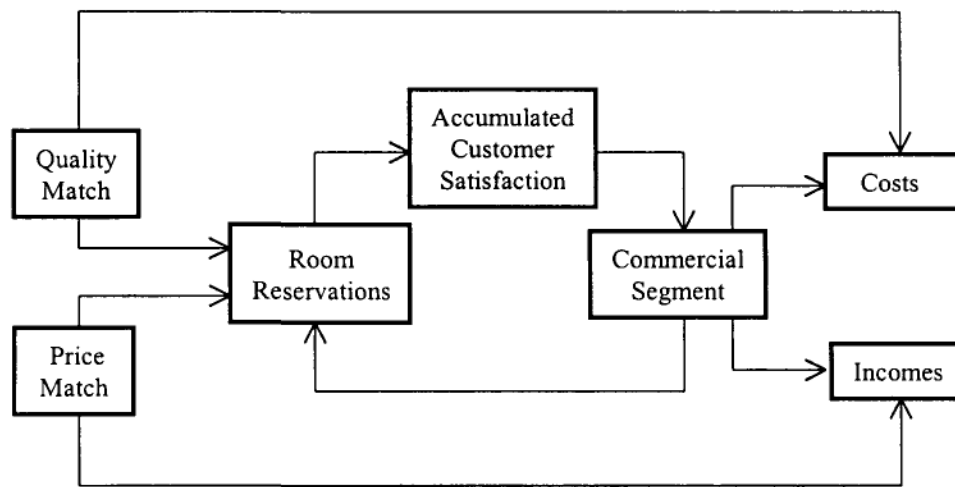
(b)

**Figure 4-3: Causal Diagram of Basic Mechanism for the Hotel Business: (a) link polarities and Change processes (b) numbered links to be narrated**



The decision-maker, based on knowledge, transforms information on *Occupancy Percentage* and *Profits* into action on *Price* and *Hotel Service Quality*. Question marks indicate unknown relationships. These relationships are elicited in the next section.

As follows, the basic mechanisms are shown in the form of **block diagram**. The complete block diagram has been fragmented in seven sectors or subsystems in order to manage the complexity of the structure: (1) Quality Match, (2) Price Match, (3) Reservations, (4) Accumulated Customer Satisfaction, (5) Commercial Segments, (6) Incomes, and (7) Costs. The sectors and their interrelations are shown in Figure 4-4. Information on *Occupancy Percentage* and *Profits* is generated by the *Commercial Segment*, *Costs* and *Incomes* subsystems. Decisions are implemented in the *Quality Match* and *Price Match* subsystems.



**Figure 4-4: Sectors and their interrelations of the hotel business model**

The subsystems were programmed using the *ithink* (HPS, 1996) software. A view of the subsystems *Quality Match* and *Price Match* are shown in Figure 4-5 and 4-6, respectively. They represent the difference between the *Service Quality* and *Price* offered by the Hotel and those demanded by the customers. The differences provoke a change in the buying incentive of the customers.

*Quality Match* subsystem obtains the discrepancies between the *Hotel Service Quality* and the quality profiles of the four type of customers. The discrepancies will produce changes in the coming next two-month number of room reservations. Based on whether the Virtual Decision-Maker is On or Off (*Fuzzy Decision-Making* equal 1 or 0), the *Hotel Service Quality* is considered coming from the machine (*QFKBS*) or a human participant (*Quality*).

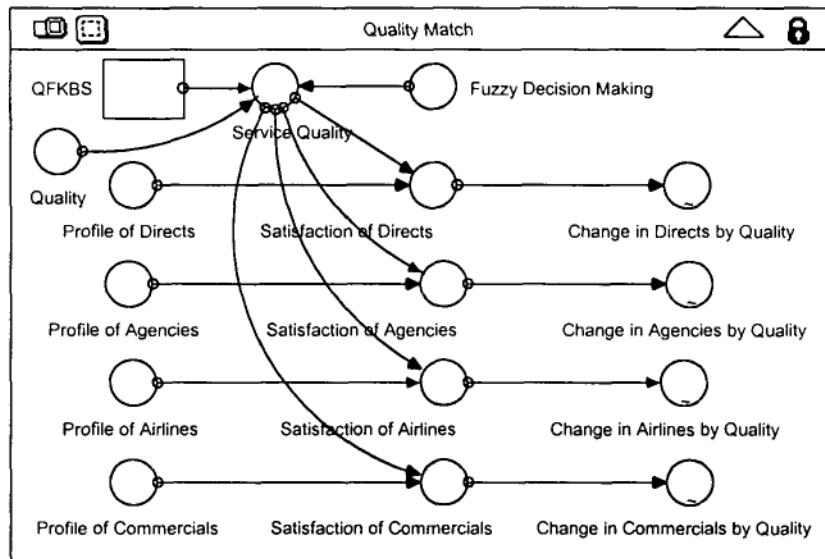


Figure 4-5: Quality Match subsystem

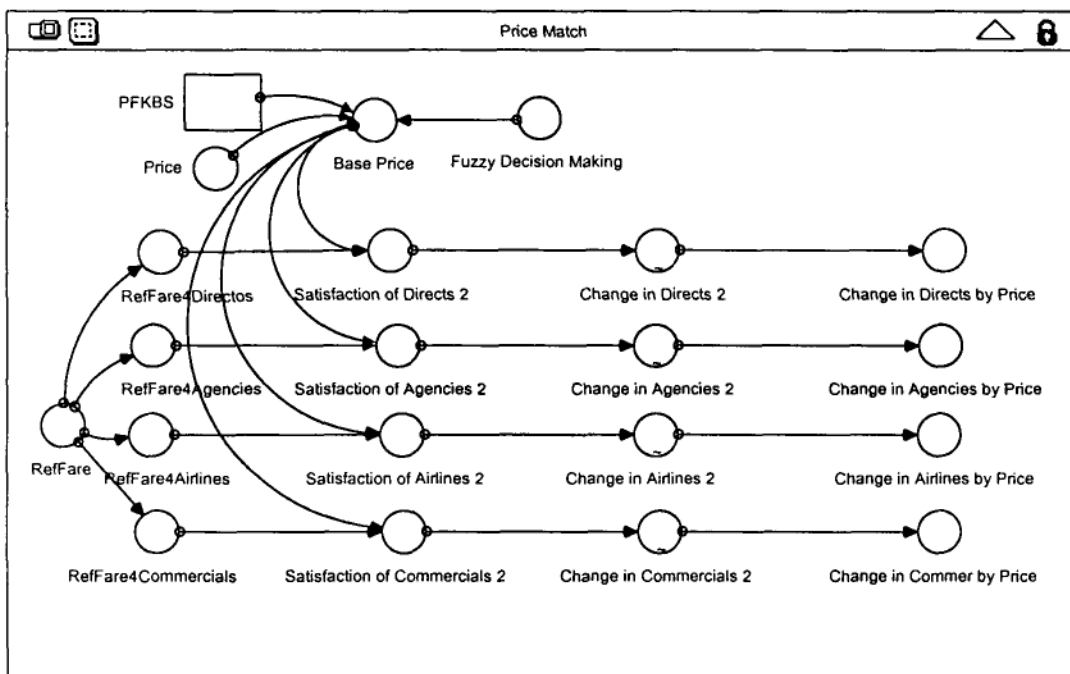
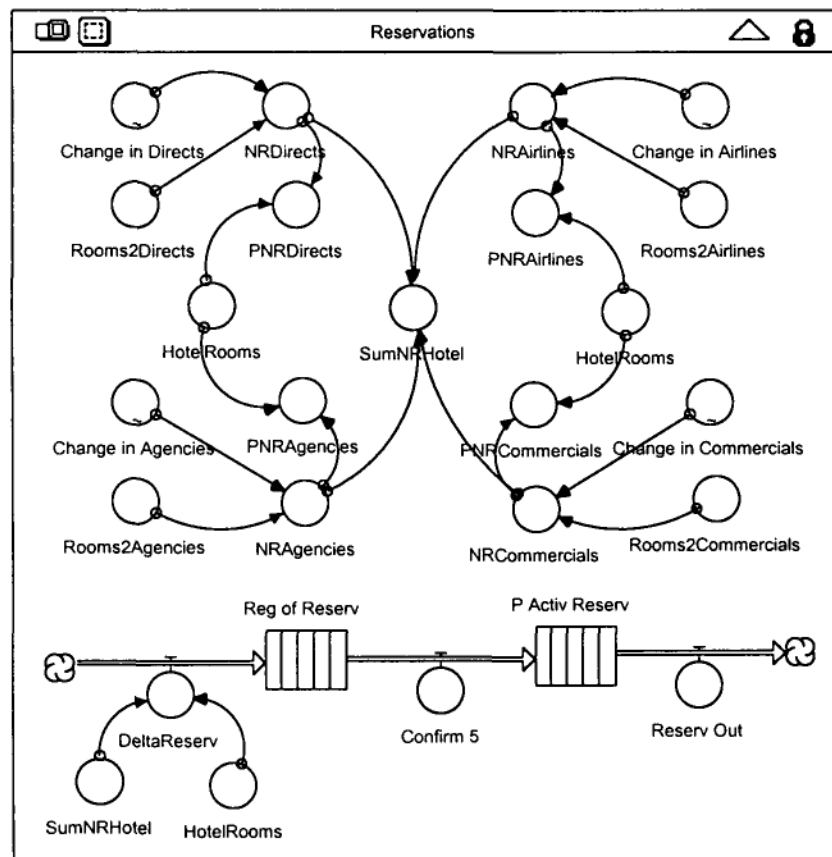


Figure 4-6: Price Match subsystem

*Price Match* subsystem obtains the discrepancies between the four prices provided by the hotel and the expected prices by the four types of customers. The discrepancies will produce changes in the coming next two-month number of room reservations. If the Virtual Decision-Maker is On or Off (*Fuzzy Decision Making* equal 1 or 0) then the *Hotel Service Quality* is taken

from the suggestion of the machine (*PFKBS*) otherwise from the suggestion of a human participant (*Price*).

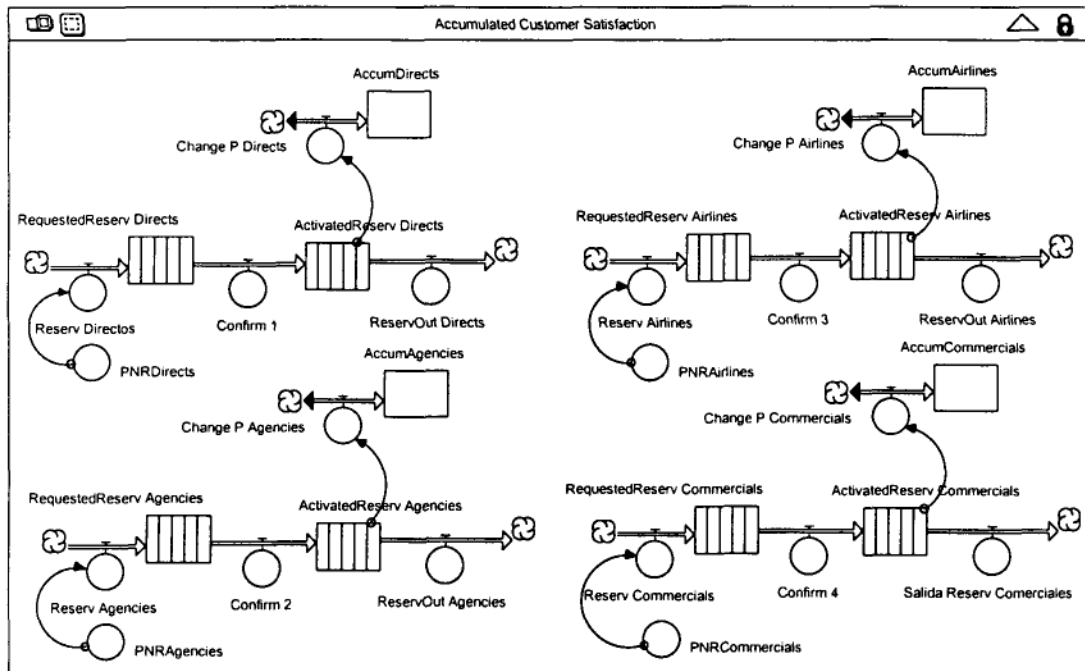
*Reservations* subsystem is shown in Figure 4-7. The subsystem processes the number of room night reservations that corresponds to each type of customer. This information represented by *NRDirects*, *NRAgencies*, *NRAirlines* and *NRCommercials* is used to calculate the percentage of increment (positive or negative) on occupied rooms in the hotel for the next two months. Number of room night reservations is obtained using the information of change in customer satisfaction caused by quality and price, and the current number of occupied hotel rooms.



**Figure 4-7: Reservation subsystem**

*Accumulated Satisfaction* subsystem is shown in Figure 4-8. This subsystem represents the core of the simulation model and processes the accumulated satisfaction of the distinctive classes of customers. The basic dynamic simulation model is formed by four first order system with delay of two time units (months). These subsystems are not independent since they share the number of customers according to the current accumulated customer satisfaction. The percentages

of room night reservations are considered as numerical indicators of the change of customer satisfaction of a specific profile in a month. The stocks named as *AccumDirects*, *AccumAgencies*, *AccumAirlines*, and *AccumCommercials* represent the accumulated customer satisfaction.



**Figure 4-8: Accumulated Customer Satisfaction subsystem**

*Commercial Segment* subsystem is shown in Figure 4-9. This subsystem computes the number of rooms that are occupied in the current month by each type of customer. This information is contained in the variables *Rooms2Directs*, *Rooms2Agencies*, *Rooms2Airlines*, and *Rooms2Commercials*. The total number of occupied hotel rooms is calculated based on data of a five-star market and the segment in percentage gained by the hotel. Both data and percentage are taken from a real data of a hotel operation in the Pacific coast of Mexico. Data and percentage are shown in next Section on Formulation of the model. In the diagram, this information is used along with the accumulated customer satisfaction to compute the number of rooms that corresponds to each type of customer. *Occupancy Percentage* is computed in this subsystem as well.

*Incomes* subsystem is shown in Figures 4-10. This subsystem calculates the flow of money that comes from the four classes of customers. The calculation involves the product of room prices times the number of corresponding rooms. All of them are accumulated in the stock named *Accumulated Incomes*. A delay of two months is considered in Agencies.

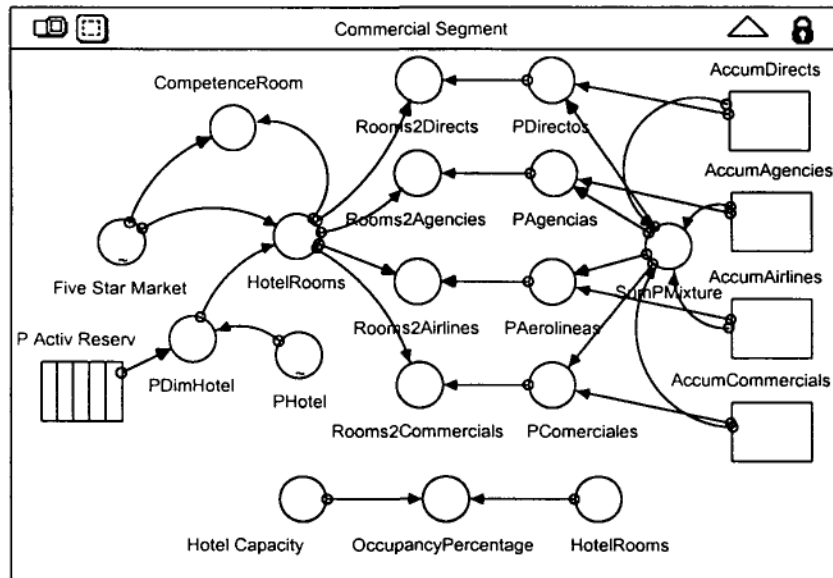


Figure 4-9: Commercial Segment subsystem

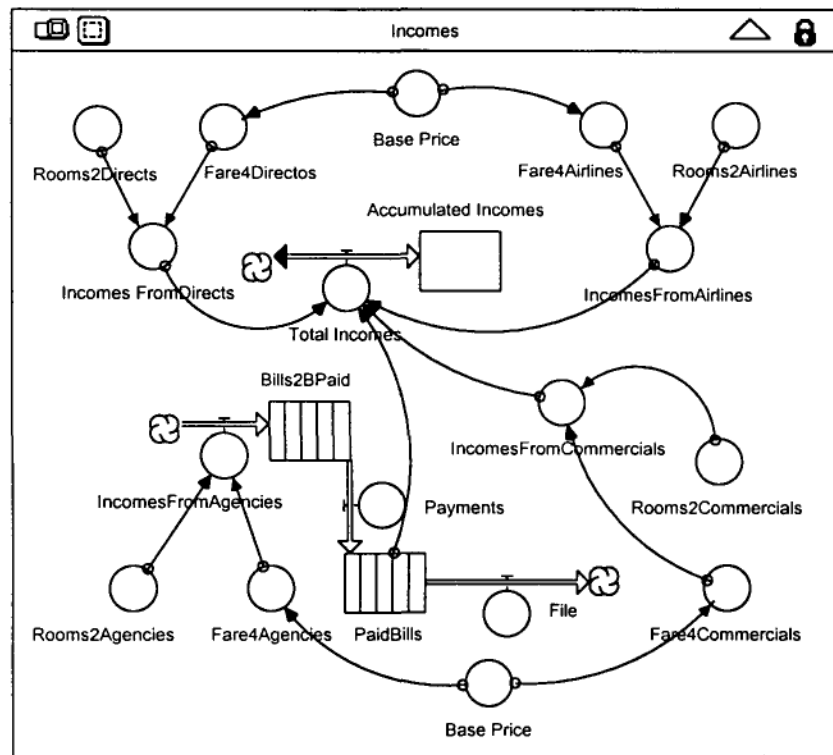


Figure 4-10: Incomes subsystem

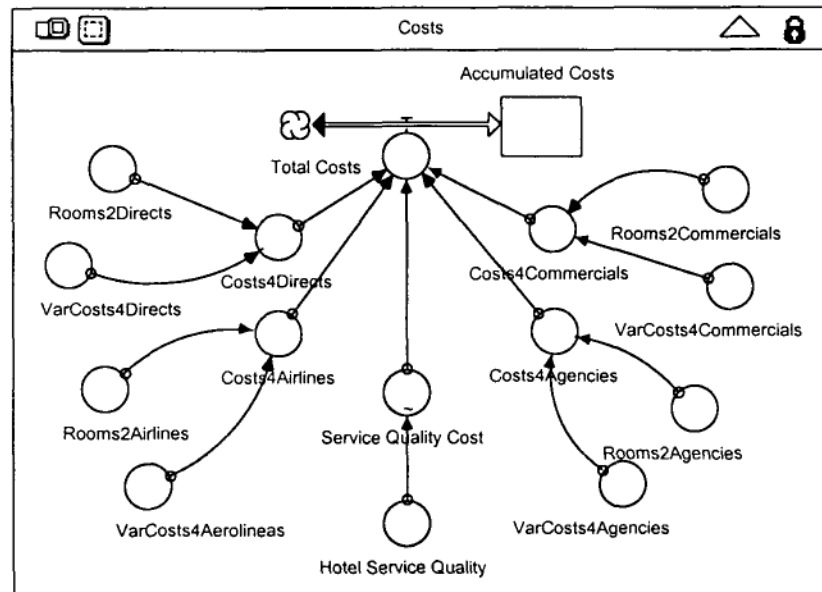


Figure 4-11: Costs subsystem

*Costs* subsystem is shown in Figure 4-11. This subsystem calculates the accumulated cost of the hotel during one year. Variable costs and fixed costs are considered. Variable costs depend on the number of customers of each type in the month. Fixed costs depend on the quality service offered by the hotel in the month also. No delays are involved in these calculations.

### 4.3.2 Formulation

The characterization of the flows and estimation of the parameter values were jointly carried out by the three members of the modeling team. The results of the process are shown by subsystems. Equations and documentation of the model are found in Appendix 2.

#### Subsystem: Quality Match

The match between *Hotel Service Quality* and *Customer Service Quality* is computed in this subsystem. *Hotel Service Quality* and *Service Quality* are quantified from 1 to 5, where five implies a quality of five stars.

The match degree is quantified in the same manner from 1 to 5. “Five” means the best match and “one” means the worst match. “Five” represents the case when the expectations of the customer are reached or surpassed. “One” represents the case when the customer is completely disappointed.

The match degree is an indicator of the customer satisfaction that leverages the reinforcing loop  $R_1$  in Figure 4-3. This loop possesses an unstable equilibrium point<sup>8</sup>. The obtained dynamic behavior is an exponential growth or decay in room reservations depending on the value of the match degree. For example, in the case of *Directs*, if the match degree is 5 then the room reservations has an exponential growth of 10% per month with regard the current occupied rooms by *Directs*. If the match degree is 1 then the room reservations has an exponential decay of 30% per month. These values are shown in Table 4-2 for the four types of customers.

**Table 4-2: Customer profile on Service Quality**

Customer type	Rate of change based on match degree for Quality (in % per month)				
	1	2	3	4	5
Directs	-30	-15	-5	-3	10
Agencies	-28	-15	-5	0	10
Airlines	-25	-15	-5	0.5	6
Commercials	-28	-15	-5	0	10

### Subsystem: Price Match

The match between offered *Prices* by the hotel and expected *Prices* by the customer is computed in this subsystem. There is a base price the hotel fixes and a reference price the customer has in mind. Offered and expected prices for each type of customer are shown in Table 4-3.

**Table 4-3: Reference prices and base prices per type of customer**

Directs	1.0 * Reference price	1.0 * Base price
Agencies	0.85 * Reference price	0.85 * Base price
Airlines	0.75 * Reference price	0.75 * Base price
Commercials	0.90 * Reference price	0.90 * Base price

Reference price is \$800.00 and base price is \$1000.00 as initial conditions in the model.

The match degree is quantified in the same manner as the case for Service Quality using a scale from 1 to 5. “Five” means the best match and “one” means the worst match. “Five”

<sup>8</sup> See Section 2.2.4 for definition of unstable equilibrium point.

represents the case when the price expectation of the customer are reached or surpassed. “One” represents the case when the customer is completely in disagreement with the price.

The match degree for price is also an indicator of the customer satisfaction that leverages the reinforcing loop  $R_1$  in Figure 4-3. This loop possesses an unstable equilibrium point, see previous footnote. The obtained dynamic behavior is an exponential growth or decay in room reservations depending on the value of the match degree. For example, in the case of *Directs*, if the match degree is 5 then the room reservations has an exponential growth of 15% per month with regard the current occupied rooms by *Directs*. These values are shown in Table 4-4.

**Table 4-4: Customer profile on Price**

Customer type	Rate of change based on match degree for Price (in % per motnh)				
	1	2	3	4	5
Directs	-30	-15	-5	0	15
Agencies	-30	-10	-5	0	15
Airlines	-35	-10	-5	0	15
Commercials	-30	-10	-5	0	15

Rates of change for the different type of customers are shown in Table 4-4. The dimensions of the values are percentage/month.

#### **Subsystem: Change in Customer Satisfaction**

Additional subsystem *Change in Customer Satisfaction* is added in order to keep the model clear.

A weighting sum of both changes caused by quality and price is carried out by this subsystem. This operation allows underlying one or other aspect in particular sessions. By default the weights are assigned equal to give same sense of importance to both changes. Mathematical expressions are the following:

$$\begin{aligned} \text{Change in Directs} &= 0.5 * \text{Changes in Directs by Quality} + 0.5 * \text{Change in Directs by} \\ &\hspace{15em} \text{Price} \\ \text{Change in Agencies} &= 0.5 * \text{Change in Agencies by Quality} + 0.5 * \text{Change in Agencies} \\ &\hspace{15em} \text{by Price} \end{aligned}$$



$$\text{Change in Airlines} = 0.5 * \text{Change in Airlines by Quality} + 0.5 * \text{Change in Airlines by Price}$$

$$\text{Change in Commercials} = 0.5 * \text{Change in Commercials by Quality} + 0.5 * \text{Change in Commercials by Price}$$

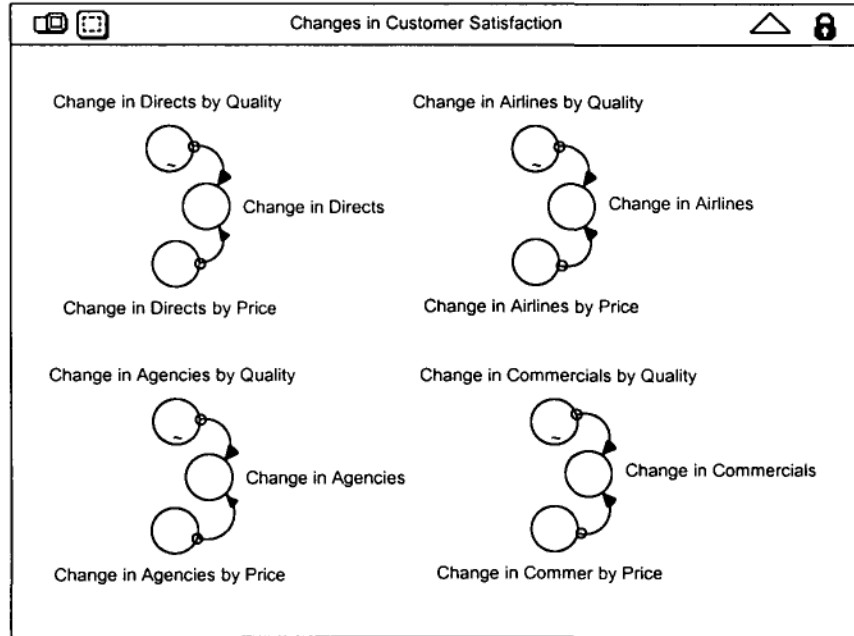


Figure 4-12: Change in Customer Satisfaction subsystem

### Subsystem: Reservations

Two relevant variables are calculated per customer in the *Reservation*:

1. Night Room Reservations
2. Fraction (percentage) of Night Room Reservations

Night Room Reservations are directly proportional the occupied rooms and the current rate of change calculated from *Quality Match* sector. For instance for *Directs* customers:

$$NRDirects = Rooms2Directs * \text{Change in Directs}$$

$$NRAgencies = Rooms2Agencies * \text{Change in Agencies}$$

$$NRAirlines = Rooms2Airlines * \text{Change in Airlines}$$

$$NRCommercials = Rooms2Commercials * \text{Change in Commercials}$$

Fraction of Night Room Reservations is the fraction of night room reservations with respect the total occupied hotel rooms. For instance for *Directs* customers:

$$PNRDirects = NRDirects / HotelRooms$$

$$PNRAgencies = NRAgencies / HotelRooms$$

$$PNRAirlines = NRAirlines / HotelRooms$$

$$PNRCommercials = NRCommercials / HotelRooms$$

### Subsystem: Accumulated Customer Satisfaction

Accumulated Customer Satisfaction for the four profiles is represented in four state equations.

$$AccumDirects(t) = AccumDirects(t - dt) + (Change P Directs) * dt$$

$$AccumAgencies(t) = AccumAgencies(t - dt) + (Change P Agencies) * dt$$

$$AccumAirlines(t) = AccumAirlines(t - dt) + (Change P Airlines) * dt$$

$$AccumCommercials(t) = AccumCommercials(t - dt) + (Change P Commercials) * dt$$

where, for example, *Change P Directs* is the *PNRDirects* of the two previous months (time unit). *PNRDirects* is the fraction (percentage) of Night Room Reservation, which is delayed before causing a change in the representative Accumulated Customer Satisfaction based on Reservations. One delay of two time units has been assigned to this process according to indications of the participants.

### Subsystem: Commercial Segment

Available data from the zone of Puerto Vallarta at Mexico establishes the boundaries for the specific hotel industry and market share during the year of 1996 in the simulator. Table 4-5 and Table 4-6 refer to the total five-stars and the hotel market share in that year, respectively (Perez-Morales, 1997-B.)

In this sector of the program, four relevant variables are computed:

1. (Occupied) Hotel Rooms
2. Occupancy Percentage
3. Competitor Rooms
4. (Hotel) Commercial Mixture
5. Occupied Rooms per Customer Profile

**Table 4-5: Regional five-star market given in numbers of night-rooms**

January	38684	July	31475
February	42005	August	31360
March	38526	September	19753
April	33854	October	25021
May	22387	November	29620
June	22387	December	30782

**Table 4-6: Percentage of the five-star market obtained by the hotel in one year**

January	0.134	July	0.130
February	0.119	August	0.122
March	0.121	September	0.131
April	0.121	October	0.113
May	0.138	November	0.132
June	0.130	December	0.178

From available real data, the region five-star market and the hotel market segment during one year were modeled. These data are shown in Tables 4-5 and 4-6. They allow modeling the effect of the seasonally behavior of this industrial sector as well as the percentage owned by the hotel. This percentage was taken as the base from which fluctuations caused by the decisions of the participants were reflected.

The number of the occupied rooms obtained by the hotel is:

$$HotelRooms = (P_{Hotel} + P_{ActivReserv}) * Five Star Market$$

where  $P_{Hotel}$  are a look up table of real data,  $P_{ActivReserv}$  is a variation from two months ago caused by decisions of the participants, and  $Five Star Market$  are the real data of the market region.

The Occupancy Percentage is computed based on the Hotel Capacity:

$$OccupancyPercentage = HotelRooms / Hotel Capacity$$

The number of rooms gained by the competitors is the complement of HotelRooms.

$$CompetitorRooms = Five Star Market - HotelRooms$$

The Commercial mixture per customer profile is given by the following expressions:

$$SumPMixture = AccumDirects + AccumAgencies + AccumAirlines + AccumCommercials$$

$$PDirects = AccumDirects / SumPMixture$$

$$PAgents = AccumAgencies / SumPMixture$$

$$PAirlines = AccumAirlines / SumPMixture$$

$$PCommercials = AccumCommercials / SumPMixture$$

The occupied rooms per customer profile is:

$$Rooms2Directs = HotelRooms * PDirects$$

$$Rooms2Agencies = HotelRooms * PAgencies$$

$$Rooms2Airlines = HotelRooms * PAirlines$$

$$Rooms2Commercials = HotelRooms * PCommercials$$

### Subsystem:Incomes

Every customer profile has its own fare:

$$Fare4Directs = 1.0 * Base Price$$

$$Fare4Agencies = 0.85 * Base Price$$

$$Fare4Airlines = 0.80 * Base Price$$

$$Fare4Commercials = 0.90 * Base Price$$

Then the incomes from each type of customer is:

$$IncomesFromDirects = Rooms2Directs * Fare4Directs$$

$$IncomesFromAirlines = Rooms2Agencies * Fare4Agencies$$

$$IncomesFromAirlines = Rooms2Airlines * Fare4Airlines$$

$$IncomesFromCommercials = Rooms2Commercials * Fare4Commercials$$

The total incomes of the month is the sum of all the four incomes per month, except incomes from agencies which has a delay of two time units.

$$Total Incomes = IncomesFromDirects +$$

$$IncomesFromAirlines + IncomesFromCommercials + PaiBills$$

where *PaidBills* is *IncomesFromAgencies* with two time delays. The total incomes are accumulated into a Stock.

**Subsystem: Costs**

Fixed and variables costs were modeled as Service Quality Cost and depending costs generated by every customer profile. Service Quality costs depends on Hotel Service Quality that operates at that time. The estimated gross values of Hotel Service Quality are the following:

**Table 4-7: Costs per month related to hotel service quality**

Hotel Service Quality (Grade)	Service Quality Cost/month (Mexican pesos)
1	1, 000, 000. 00
2	1, 500, 000. 00
3	2, 000, 000. 00
4	2, 500, 000.00
5	3, 200, 000. 00

Different customer profile generates different variable cost per unit.

$$VarCost4Directs = 220$$

$$VarCost4Agencies = VarCost4Airlines = VarCost4Commercials = 200$$

The costs per customer profile is then:

$$Costs4Directs = VarCosts4Directs * Rooms2Directs$$

$$Costs4Agencies = VarCosts4Agencies * Rooms2Agencies$$

$$Costs4Airlines = VarCosts4Airlines * Rooms2Airlines$$

$$Costs4Commercials = VarCosts4Commercials * Rooms2Commercials$$

The accumulated cost is computed into a stock named *Accumulated Costs*.

**4.3.3 Testing**

The reference modes and the simulated behavior of the hotel are compared in this subsection to validate the model. The reference modes are the hypotheses of the dynamic behavior of the hotel. They were presented in Section 4.3.1 and exposed in Figures 4-2 (a), (b), and (c).

The simulated behavior is presented as follows based on a graphical sensitivity analysis. Changes on customer satisfaction and profits are observed under changes on Quality and Price. The first set of graphics, Figures 4-13 to 4-18, corresponds to the effects caused by offering a

Hotel Service Quality of 1, 4, and 5 stars. The base price was fixed at \$1000.00 pesos for the three cases. By offering a quality degree of one, the customer satisfaction declines for the 4 types of customers, see Figure 4-13. This means that quality and price are not matching. The offered quality is different from that one expected for a price of \$1000.00. Profits are mostly negative for the operation year and it is shown in Figure 4.14.

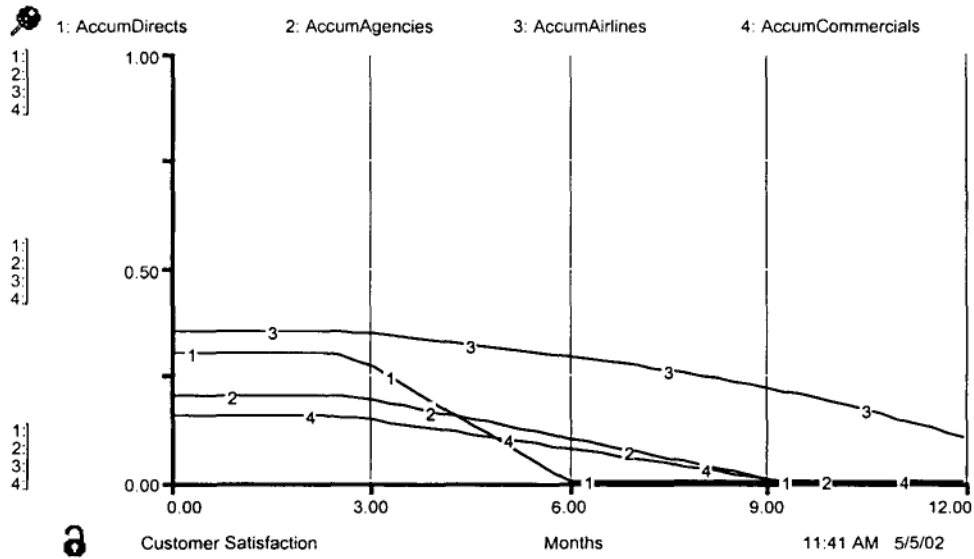


Figure 4-13: Accumulated Customer Satisfaction (Quality Service = 1)

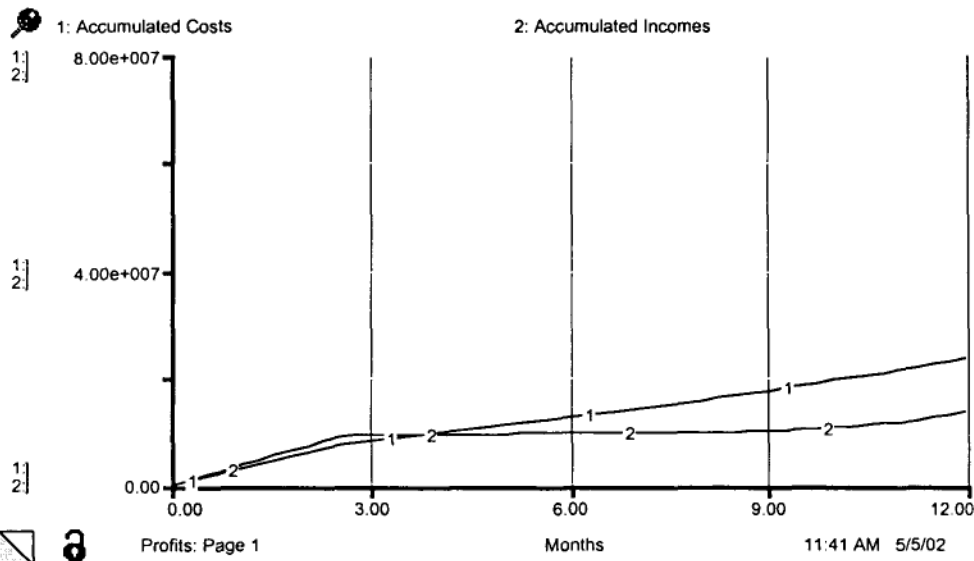


Figure 4-14: Accumulated Incomes and Costs (Quality Service = 1)

Figures 4-15 and 4-16 refer to a quality degree of four. Figures 4-17 and 4-18 refer to a quality degree of five stars. It seems that a price of \$1000.00 along with a five star quality is a good combination. However, it could be improved by adjusting them during the year instead of sustaining just fixed value.

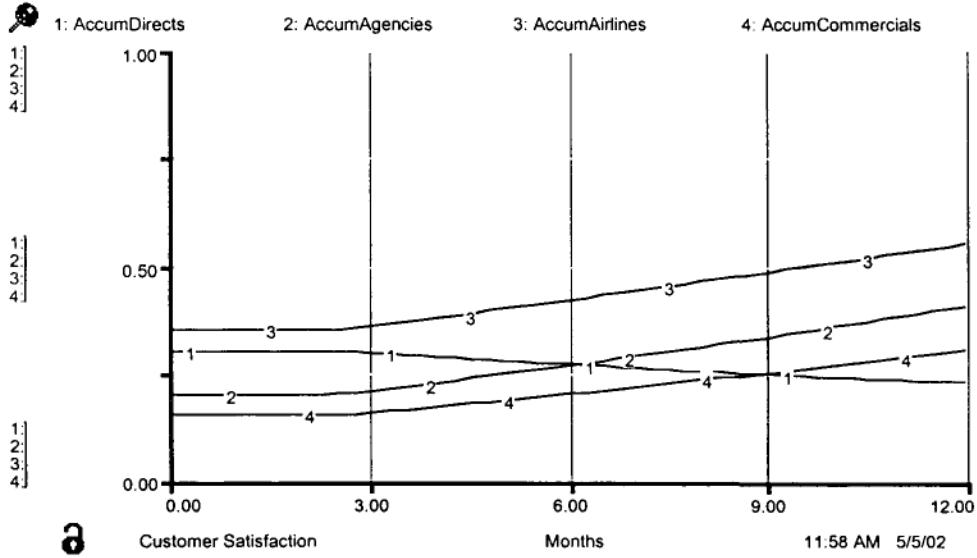


Figure 4-15: Accumulated Customer Satisfaction (Quality Service = 4)

Four star in *Quality Service* satisfies three out of the four profiles of the customers. Only *Directs* profile seems unsatisfied by this degree of service. It can be observed a sustained profit during the last eight months.

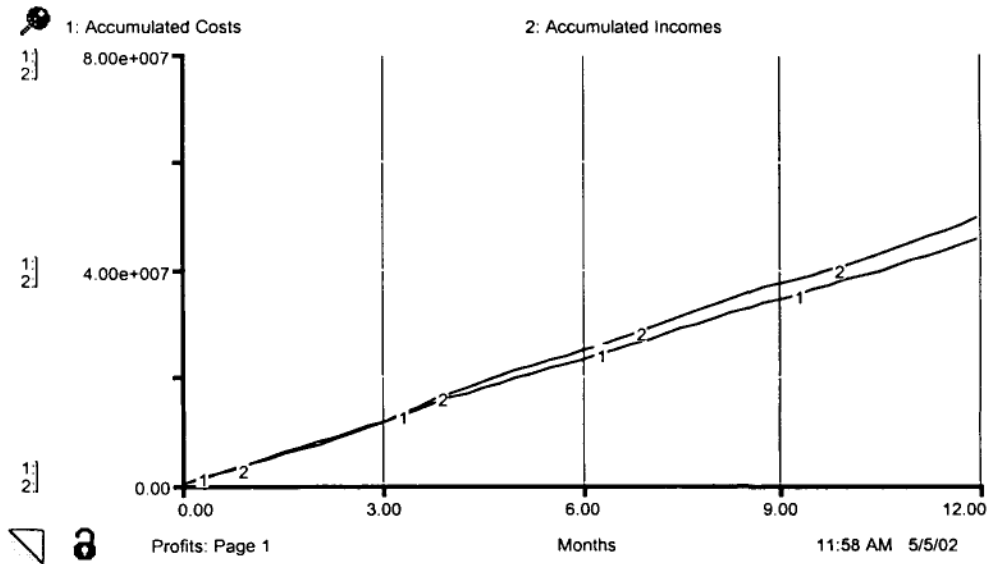


Figure 4-16: Accumulated Incomes and Costs (Quality Service = 4)

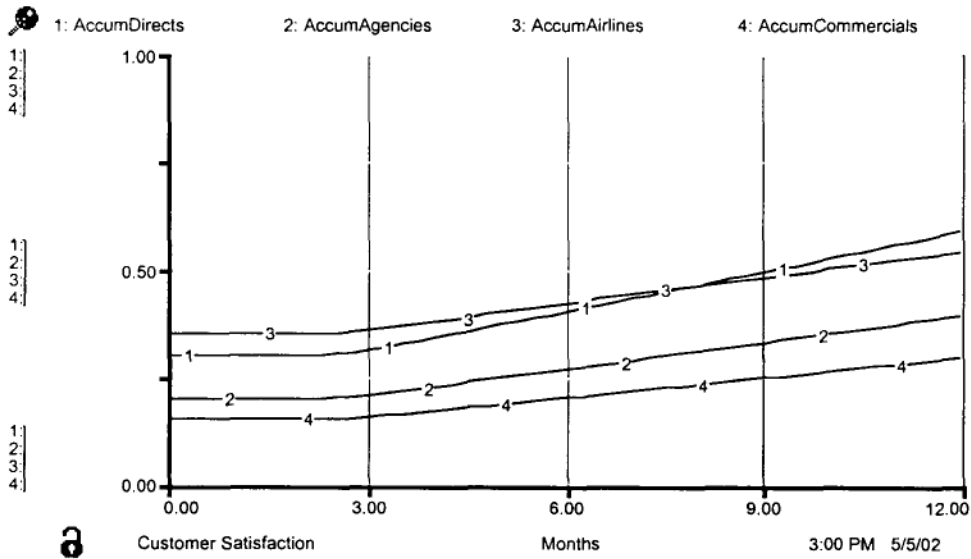


Figure 4-17: Accumulated Customer Satisfaction (Quality Service = 5)

Five Star *Quality Service* makes a good match with the price of \$1000.00. The needs of the customers are satisfied and positive number of business are running during almost 9 months of the year.

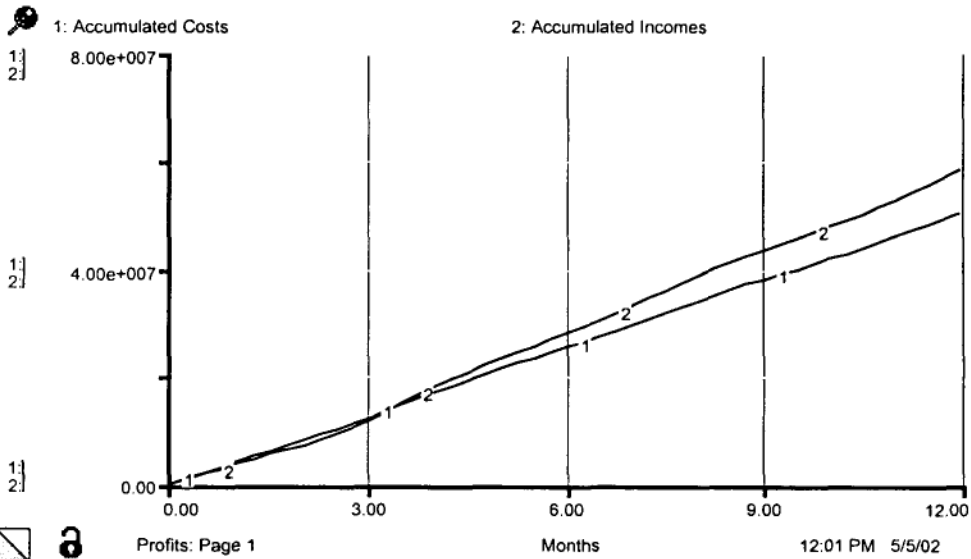


Figure 4-18: Accumulated Incomes and Costs (Quality Service = 5)

The second set of graphics corresponds to the effect caused by assigning different prices to a fixed quality degree. The *Hotel Service Quality* is fixed in three stars and prices are assigned on a base of \$800.00, \$1000.00, and \$1400.00. The corresponding Figures are 4-19 and 4-20, 4-21 and 4-22, and finally 4-23 and 4-24, respectively. The lower the price, the higher the customer



satisfaction is. The lower the price, the lower the profit is in the short-term and it might be also in the long-term.

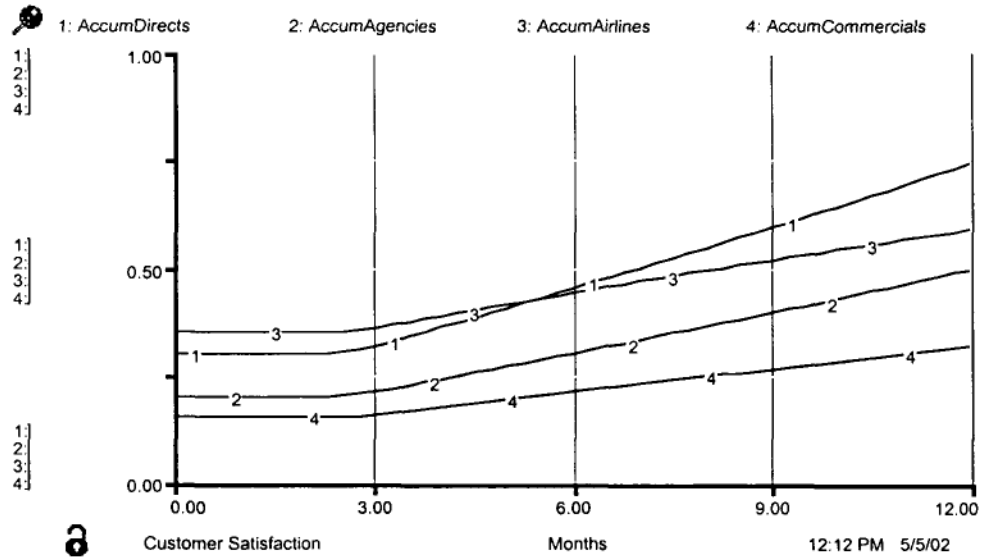


Figure 4-19: Accumulated Customer Satisfaction (Base Price = 0800)

The four kinds of customers are completely satisfied with the *Price* of \$800.00 and *Service Quality of three*. Profits are reasonable good. However, the equilibrium point is farther in the time. It is around the fifth month.

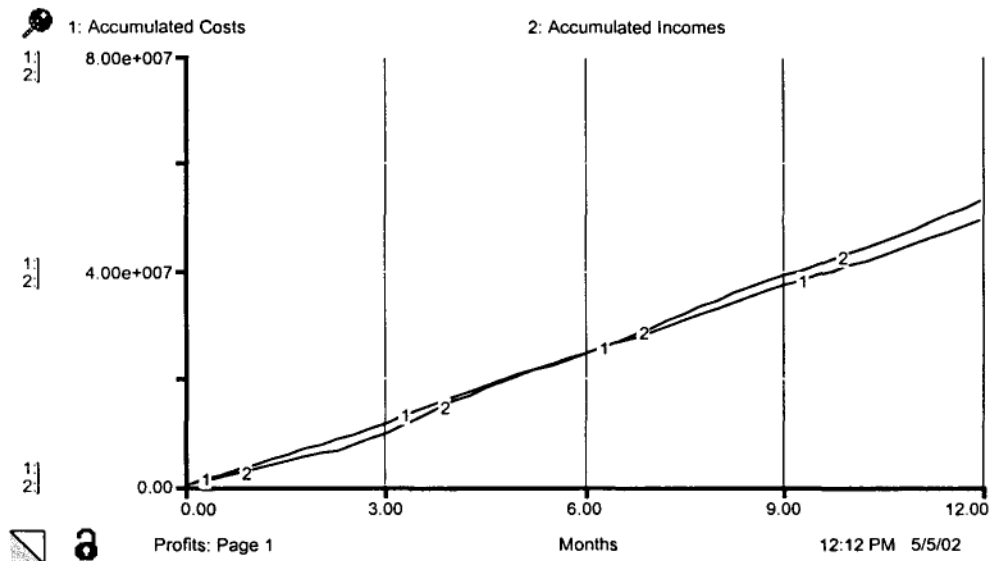


Figure 4-20: Accumulated Incomes and Costs (Base Price = 0800)

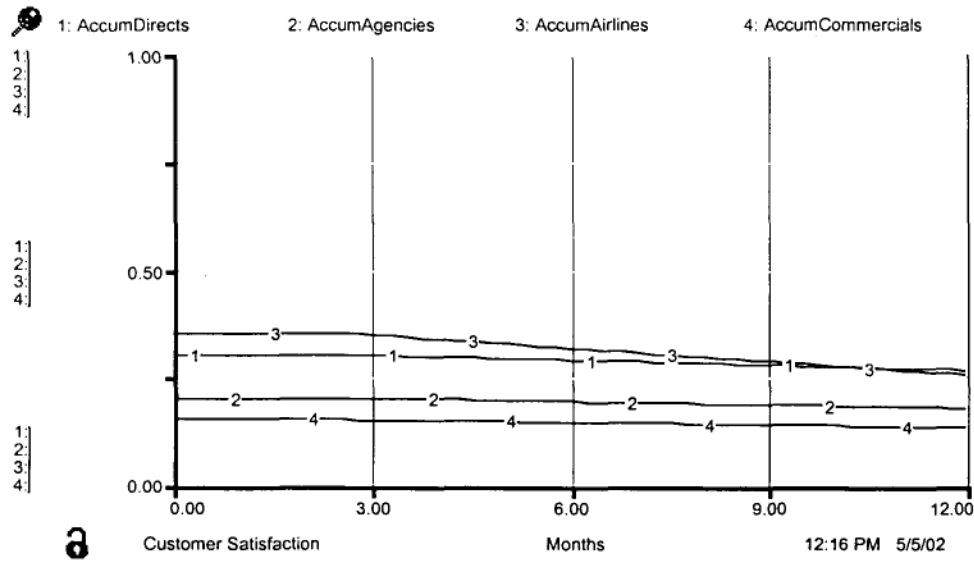


Figure 4-21: Accumulated Customer Satisfaction (Base Price = 1000)

A Price of \$1,000.00 with *Quality* of three suggests not a very good idea in terms of business. Most of the times *Cost* are higher than *Incomes*, Three profiles of clients are unsatisfied.

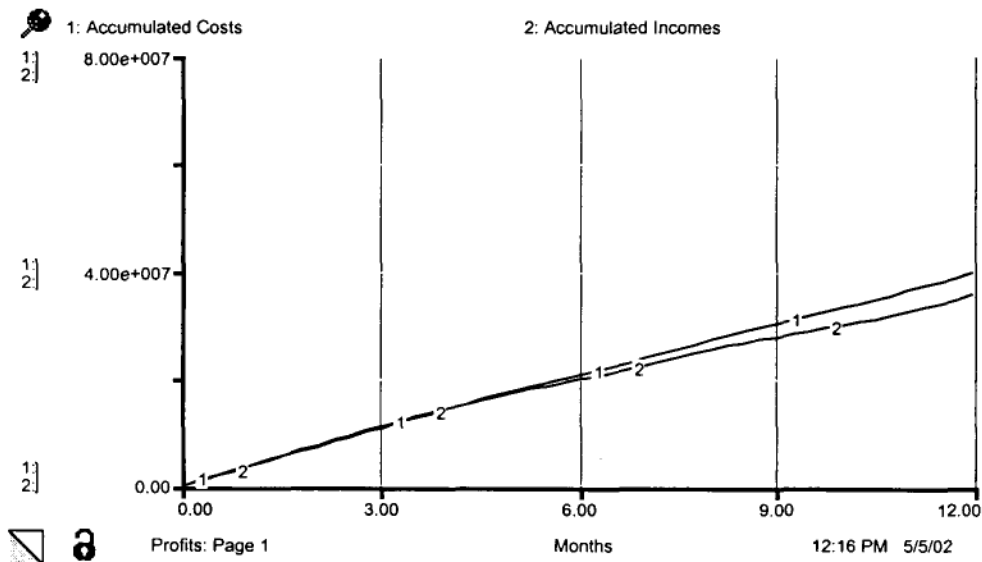


Figure 4-22: Accumulated Incomes and Costs (Base Price = 1000)

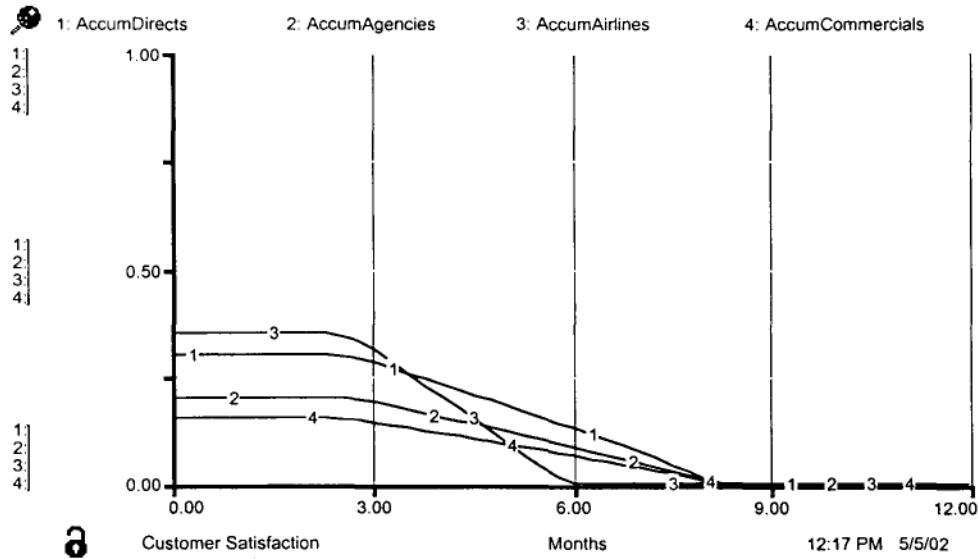


Figure 4-23: Accumulated Customer Satisfaction (Base Price = 1400)

The customers are completely unsatisfied with the combination of a *Price* of \$1400.00 and *Quality Service* of 3 stars. In Figure 4-23, this perception is illustrated. There is no satisfied customer after month 9. *Profits*, which are shown in Figure 4-24 are negative most part of the year.

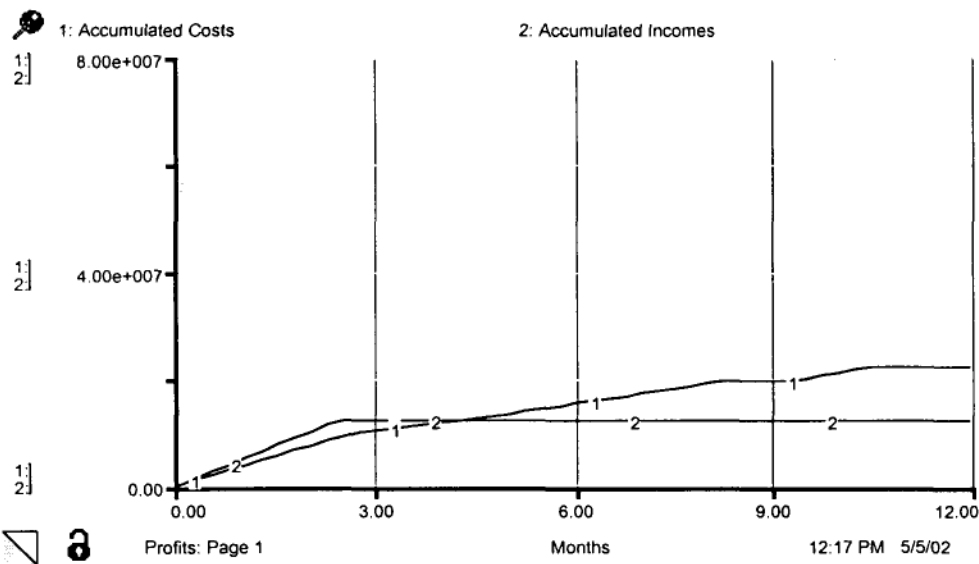


Figure 4-24: Accumulated Incomes and Costs (Base Price = 1400)

The results respond to the reference modes and show at the same time the sensitivity to the different *Hotel Service Quality* grades. Parameters such as rate of change in *Quality Match* sector, and cost, fixed and variable, in *Cost* sector were adjusted until the model generates confidence on

the key variables behavior according to the experience and mental models of the specialized participants.

In synthesis, the model represents the hypothesis that all the customers will be satisfied when the hotel offers the best *Service Quality*, that is quality degree 5 with the lowest price. However, this does not guarantee the maximum profit. The participants will have to find the best equilibrium point in order to achieve their goal of profit, customer satisfaction, and time for their return of investment. Participants, with no previous warning about this behavior, will have to find it during a seminar on managerial skills and discover counterintuitive ideas. The model and the interrelations of factors will help them to shape discussions in learning sessions. In this form, knowledge and experiences could be transmitted and administrated in global organizations via simulators and experience sessions.

#### 4.3.4 Implementation

The implementation phase conventionally has the purpose of (1) usage of the model to improve understanding of the problematic situation and (2) discover policies that make the situation better than it currently is.

In the particular case of this research, the model does not have those purposes. It rather follows the third purpose: to capture mental models and serve as a communication instrument, described in Section 2.4.3, in the first stage, first step: *Define the model purpose*.

Now the hotel model will be part of a larger system. This larger system includes the interactions and change processes between the hotel model and a virtual decision-maker. The virtual decision-maker will be built using a set of fuzzy rules that pretend to manage the hotel. First, the set of rules for effective management has to be acquired. This implies a second round of Qualitative Knowledge Acquisition. The focus or attention is now paid on how to explicit the basic rules used by a human manager to transform information into actions.

In the next Section, the implementation of the virtual decision-maker is described in detail.

#### 4.4 Decision Making Policies Representation Using Fuzzy Logic

The objective of this section is to show the application and results of the method for policy representation using Fuzzy Logic described in Section 3.3. The method follows three steps: (1) elicitation of policies from the decision-makers, (2) codification of the policies in a computer, and (3) utilization of the policies in computational models to respond and generate new questions.

The scope is limited to establish the management or control of a hotel business process (HBP) to achieve goals on profits and occupancy percentage, see Figure 4-25. The interactions and processes of two subsystems comprise the whole: (1) Hotel subsystem and (2) Decision-maker subsystem, which can be human or artificial (virtual) kind.

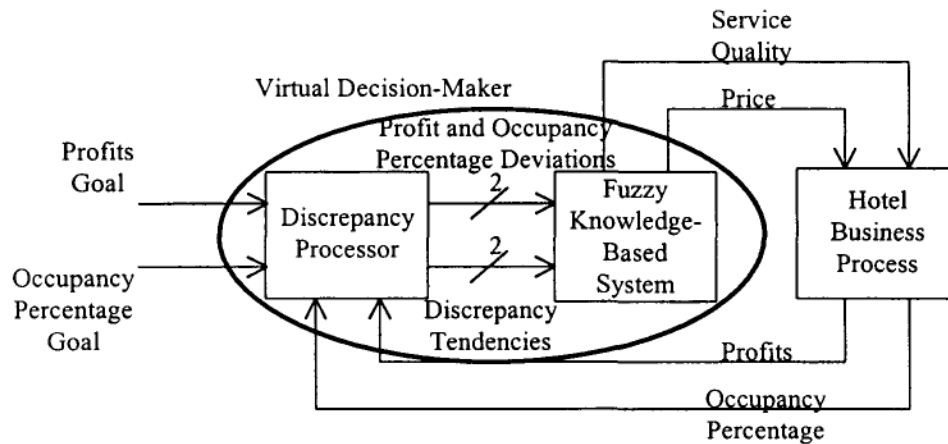


Figure 4-25: Goal Seeking System for the Hotel Business and Administration

On one side, the HBP is considered a Multiple Input Multiple Output (MIMO) system of  $2 \times 2$ , see Figure 4-26. The input variables are *Service Quality* and *Price*. The output variables are *Occupancy Percentage* and *Profits*. Their operational definitions appear as follows.

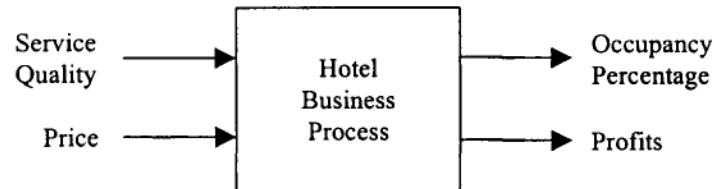


Figure 4-26: Hotel Business Process as a square system  $2 \times 2$

- *Service Quality* refers in this research and according to the participants to the serviced accommodation. Hotels are graded from one to five stars. Thus, it was defined that *Service*

*Quality* had this operational rank in the model. This rank is adopted form "The World Tourism Organization (WTO) model, which is generally accepted in most countries. The general rating scheme for hotels (Lawson, 1995, cited by Ingram, 1996, 32) is shown in Table 4-8.

- *Price* refers to the base price of the hotel. Different prices for different customer profiles are assigned taking into account the base price, see Table 4-3.
- *Occupancy Percentage* refers to the percentage given by the relationship between current occupied rooms over the total available rooms, named hotel capacity, of the hotel.
- *Profits* refer to the net profit generated by the hotel. It is the difference between aggregate Incomes and Costs. Incomes include the revenue mix of rooms, food, beverages, and rentals. The term Costs include variable and fixed costs or charges. Variable costs include departmental cost of sales, departmental payroll and related expanses on rooms, food, and beverages. Also undistributed operating expanses, such as, administration, marketing, property operation, maintenance, energy. Fixed costs include rent and depreciation (Medlik and Ingram, 2001, 139.)

**Table 4-8: Quality Service based on the WTO rating scheme**

Stars	General Characteristics
1	"Hotels with good basic facilities and furnishings ensuring comfortable accommodation. Meal services may be limited. Includes small private hotels."
2	"Hotels having higher standards of accommodation and more facilities providing good levels of comfort and amenity. Includes private hotels and budget accommodation."
3	"Well appointed hotels with spacious, very comfortable accommodation, mostly with en-suite bathrooms. Full meal facilities are provided as well as a range of amenities."
4	"High quality hotels, well equipped and furnished to a very high standard of comfort, offering a very wide range of services and amenities for guests and visitors."
5	"Outstanding hotels with exceptional quality accommodation and furnishings to the highest international standards of luxury, providing impeccable services and extensive amenities."

(Ingram, 1996, 32)

On the other side, the decision-making policies, which control the process, are represented by a Fuzzy Knowledge-Based System (FKBS) with four inputs and two outputs as it shown in Figure 4-25. Description of the used FKBS is presented in Section 2.3.3, specifically for the design of the Virtual Decision-Maker in Section 2.3.4. The input variables are the two discrepancies between desired and current conditions of profits and occupancy percentages, and the two tendencies of both discrepancies. The output variables are the suggested price and service quality recommended by the FKBS called Virtual Decision-Maker during the interaction with the participants.

#### 4.4.1 Step 1 Elicitation of Policies from the Decision-Makers

##### 1. Select the set of conditions or variables you want to manage

The selected variables are:

- *Profits*
- *Occupancy Percentage*

*Profits* are considered as an indicator of how well the business is going on its objective of generating wealth. It reflects the fast dynamics of the system. *Occupancy Percentage* is an indicator of the number of clients that possesses the business. It represents the intangible asset of customer satisfaction. This indicator refers to the slow dynamics of the system. It takes a longer time than that one required by *Profits* to increase or decrease.

Both managed variables *Profits* and *Occupancy Percentage* are accessible in the model as well as in the reality.

##### 2. Select the set of goal values for such conditions

The selected goals to be achieved in the following twelve months are:

- *Profits*: 5% higher than those obtained last year
- *Occupancy Percentage*: 10% higher than the one obtained last year

##### 3. Select the variables that will allow decisions be implemented

The variables that will drive the business-managed variables are:

- *Price*
- *Service Quality*.

#### 4. Sketch a hypothetical curve of the deviation time response for each managed variable

Behavior hypothesis of *Profit Deviation* and *Occupancy Percentage Deviation* are sketched in Figures 4-27 (a) and (b). Both variables are not independent each other and the sketches attempt to bring into possible states to elicit decision rules. The deviation behavior sketch along with its explanation can omit the sketches of desired and current conditions as well as tendency description. Signal of deviation behavior is a rich enough information to make decisions. The study of deviation signals is useful for linear and non-linear system analysis.

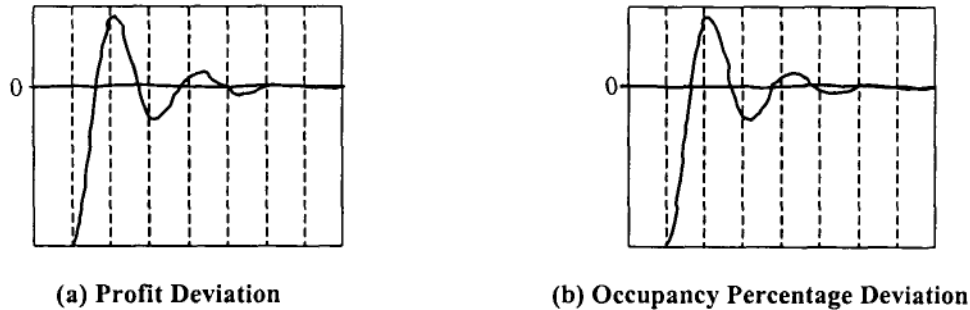


Figure 4-27: Sketches of deviation signals

#### 5. Make clear the meaning of the variables: *Deviation* and *Tendency of deviation*

*Deviation* ( $e$ ) and *Tendency of deviation* ( $\dot{e}$ ) are explained with the previous sketched response in Figures 4-27 (a) and (b). The following expressions:

$$e = \text{perceived condition} - \text{desired condition}$$

$$\dot{e} = d e(t)/dt$$

It should be clear to the participants that most of the policies used for them to make decisions through the time, limited by the scope of the modeling effort, will be considered during the session to acquire the policies with these two sketches.

#### 6. Select two or three, at most, fuzzy sets for deviation and tendency deviation variables

Two linguistic values (fuzzy sets) *Negative* and *Positive* have been selected for every linguistic variable (1) *Profit Deviation*, (2) *Occupancy Percentage Deviation*, (3) *Profit Deviation Tendency*, and (4) *Occupancy Percentage Tendency Deviation*. The two linguistic values are illustrated in Figure 4-28. The parameters for every linguistic variable are presented in Table 4-9. The parameters represent the generic fuzzy partitions in this case.



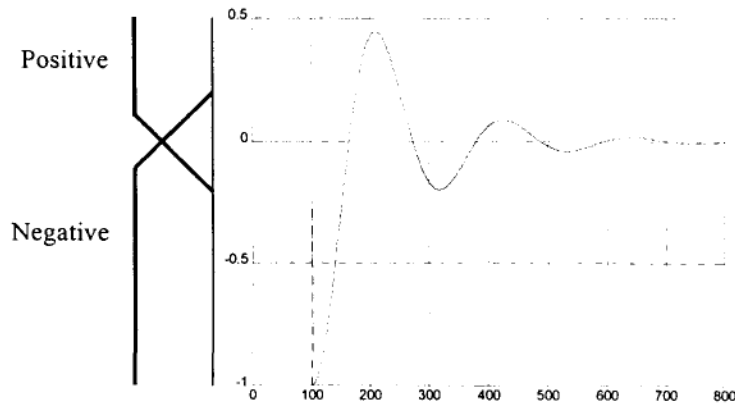


Figure 4-28: Two linguistic values Negative and Positive

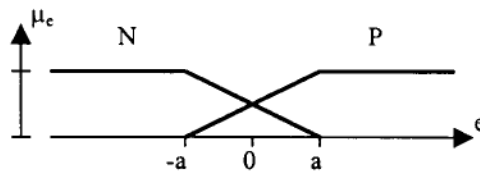


Figure 4-29: Two fuzzy sets and one parameter to handle the linguistic variable "e"

Two initial questions were formulated. (1) Are two fuzzy sets enough? (2) Is one parameter enough to handle the two fuzzy sets? Both questions were affirmatively answered by experimental results. Later on the research, the reference (Viljamaa and Koivo, 1993) was found with the same proposition for a different process and with satisfactory results as well. After a detailed analysis the conclusion is the fuzzy structure is generic to represent control laws for systems with two inputs and two outputs.

Table 4-9: Parameter values for input linguistic variables

Linguistic Variable	Value of parameter "a"
<i>Occupancy Percentage Deviation</i>	10 %
<i>Occupancy Percentage Tendency Deviation</i>	5 % per month
<i>Profit Deviation</i>	5 %
<i>Profit Tendency Deviation</i>	10 % per month

### 7. Select two or three singletons, at most, as linguistic values for the driving variables

*Increment in Price* and *Increment in Service Quality* have been chosen to be the linguistic variables for the driving variables *Price* and *Service Quality*. Three singletons *Negative* (N), *Zero* (Z), and *Positive* (P) are selected as linguistic values for the two linguistic variables. The size of big or small in a positive or negative change should be established for the participants and adjusted by the knowledge engineer during the codification step. This process of adjusting parameters is described with detail in Section 4.3.3. The set of three singletons is showed in Figures 4-30 and 4-31 for *Increment in Price*.

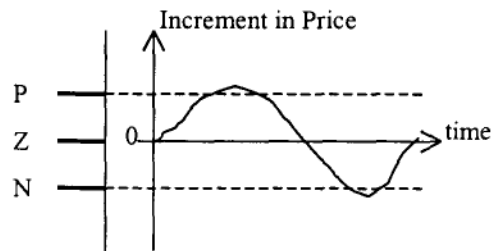


Figure 4-30: Three singletons are the fuzzy sets for the driving variables

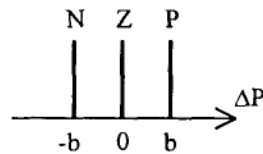


Figure 4-31: Three linguistic values for the output linguistic variable  $\Delta P$

The singletons values  $b$ , see Figure 4-31, that are presented in Table 4-10 were founded after a process of adjustment by trial and error. This process was improved later by adding an adaptive mechanism that adjusts the singletons automatically according the system performance. This adaptive mechanism is described in detail in Section 4.4.

Table 4-10: Singleton values for output linguistic variables

Variable \ Values	Negative (N)	Zero (Z)	Positive (P)
Increment in Price ( $\Delta P$ )	-100	0	100
Increment in Service Quality ( $\Delta SQ$ )	-0.8	0	+0.8

### 8. Represent the knowledge of the manager as policies using if-then rules

The FKBS structure that supports the *Virtual Decision-Maker* subsystem is shown in Figure 4-32.

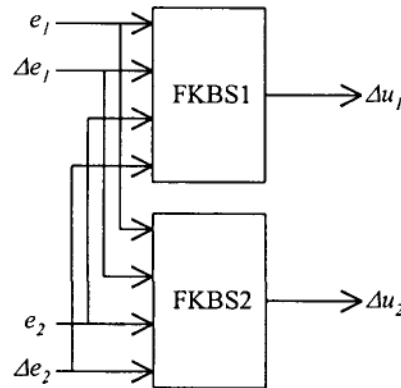


Figure 4-32: FKBS structure for the Virtual Decision-Maker

where:

- $e_1$  - Occupancy Percentage Deviation
- $\Delta e_1$  - Occupancy Percentage Tendency Deviation
- $e_2$  - Profit Deviation
- $\Delta e_2$  - Profit Tendency Deviation
- $\Delta u_1$  - Increment in Service Quality
- $\Delta u_2$  - Increment in Price

This structure has the practical advantage, over the other structures shown in Figure 2-8, that it allows eliciting and representing the decision rules in an aggregate and meaningful way for people. Every decision depends on the interrelated deviations and tendency deviations from the goals of the important variables. Both decisions  $\Delta u_1$  and  $\Delta u_2$  are coupled by the information of the deviations. For structure (a) in Figure 2-8, the decision rules should additionally include autoregressive information about values of past decisions, which is not the most usual way of thinking. For structure (c) in Figure 2-8, an isolated and not coupled analysis of every deviation information should be carried out first by later assembling the conclusions and generate final decisions. This involves too much analytical effort for this case and it would require deep knowledge about cognitive laws about how people join conclusions. So from the aggregate and

meaningful point of view, the structure (b) in Figure 2-8, which is represented in Figure 4-32, is the best practical option.

**Table 4-11: Fuzzy Knowledge Base**

Rule	$e_1$	$\Delta e_1$	$e_2$	$\Delta e_2$	$\Delta u_1$	$\Delta u_2$
1.	N	N	N	N	P	Z
2.	N	N	N	P	P	N
3.	N	N	P	N	P	N
4.	N	N	P	P	P	N
5.	N	P	N	N	Z	P
6.	N	P	N	P	Z	Z
7.	N	P	P	N	Z	Z
8.	N	P	P	P	Z	N
9.	P	N	N	N	Z	P
10.	P	N	N	P	Z	Z
11.	P	N	P	N	Z	Z
12.	P	N	P	P	Z	N
13.	P	P	N	N	Z	P
14.	P	P	N	P	Z	P
15.	P	P	P	N	Z	P
16.	P	P	P	P	N	Z

The premises of the if-then rules are  $e_1$ ,  $\Delta e_1$ ,  $e_2$ , and  $\Delta e_2$ . The consequents are  $\Delta u_1$  and  $\Delta u_2$ .

The design criteria described in Section 2.3.4 to construct a Virtual Decision-Maker are applied. The objective is to acquire qualitative knowledge used in policies and represent it in a Fuzzy Knowledge Base form.

The total number of if-then rules that conforms the complete state space is 16 since there are 4 linguistic values with 2 value each. By questioning the corresponding actions for every state, Table 2-1 (in Section 2.3.4) is filled. The use of the hypothetical behavior sketches by the knowledge engineer with the participants is essential in this part of the process. The final result is the Fuzzy Knowledge Base shown in Table 4-11.

## 4.4.2 Step 2 Codification of the Policies in a Computer

### 9. Application of Mamdani's fuzzy model

Three processes are codified:

1. Fuzzification
2. Inference
3. Defuzzification

#### Fuzzification

This process has been codified following the description in Section 3.3.3 for the case of two linguistic values and considering the value of parameter "a" for each linguistic variable as defined in number 6 of this section.

The membership functions for the fuzzy sets, shown in Figure 4.29, are defined by:

$$\mu_e N = \begin{cases} 1 & ; e < -a \\ \frac{a-e}{2a} & ; -a \leq e \leq a \\ 0 & ; e > a \end{cases} \quad \mu_e P = \begin{cases} 0 & ; e < -a \\ \frac{a+e}{2a} & ; -a \leq e \leq a \\ 1 & ; e > a \end{cases}$$

The process is implemented in the Sector "Fuzzification", which is exposed in Figure 4-33. Equations of the model are included in Appendix 1.

Occupancy Percentage Deviation is calculated in *Occ Perc Gap* by realizing the difference between the *Occupancy Goal* and current *Occupancy Percentage*. Then  $e_1$  and  $e_1dot$ , which are  $e_1$  and  $\Delta e_1$  are fuzzified. Variables  $x1NV$  and  $x1PV$  are the membership degree Negative and Positive, respectively for  $e_1$ . Variables  $x1Nvdot$  and  $x1Pvdot$ , for  $\Delta e_1$ .

Profit Deviation is calculated in *Profit Gap* by realizing the difference between the *Profit Goal* and current *Profit*. Then  $e_2$  and  $e_2dot$ , which are  $e_2$  and  $\Delta e_2$ , are fuzzified. Variables  $x2NV$  and  $x2PV$  are the membership degree Negative and Positive, respectively for  $e_2$ . Variables  $x2Nvdot$  and  $x2Pvdot$ , for  $\Delta e_2$ .

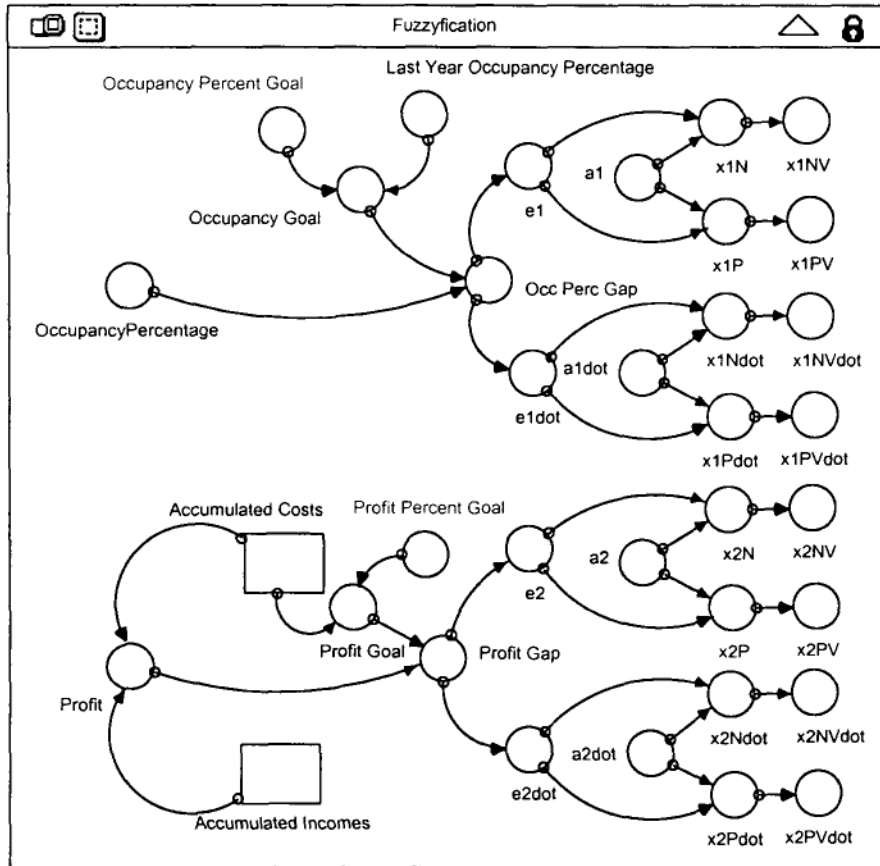


Figure 4-33: Sector "Fuzzification"

**Inference**

The Mamdani's fuzzy model is implemented and the Max-Min operations are used for this purpose. The Min operation is applied to conclude in every single if-then rule. The Max operation is applied to solve conflicts among the obtained conclusions.

The codification of the sixteen if-then rules to form the Fuzzy Knowledge Base, see Table 4-11, is shown in Figure 4-34. Four blocks of fuzzy rules appear in Figure 4-34. Every block contains eight rules. Four of them are for *Increment in Service Quality* ( $\Delta u_1$ ) and 4 for *Increment in Price* ( $\Delta u_2$ ). The consequents for *Increment in Service Quality* rules are identified by  $qw_i$  and for *Increment in Price* are identified by  $pw_i$ . The premises appear at the center with an initial  $x$  as identifier. Min operations are carried out in the converters  $qw_i$ s and  $pw_i$ s which are the conclusions for every rule. Following the number of rules presented in Table 4-11, the block on the left top corner contains rules 1-4; the block on the right top corner contains rules 5-8; block on

the left bottom corner contains rules 9-12, and block on the right bottom corner contains rules 13-16. *Min* operator is used to obtain the conclusion value.

The expression for *qw1* is:

$$qw1 = \min(x2NV, x2NVdot, x1NV, x1NVdot)$$

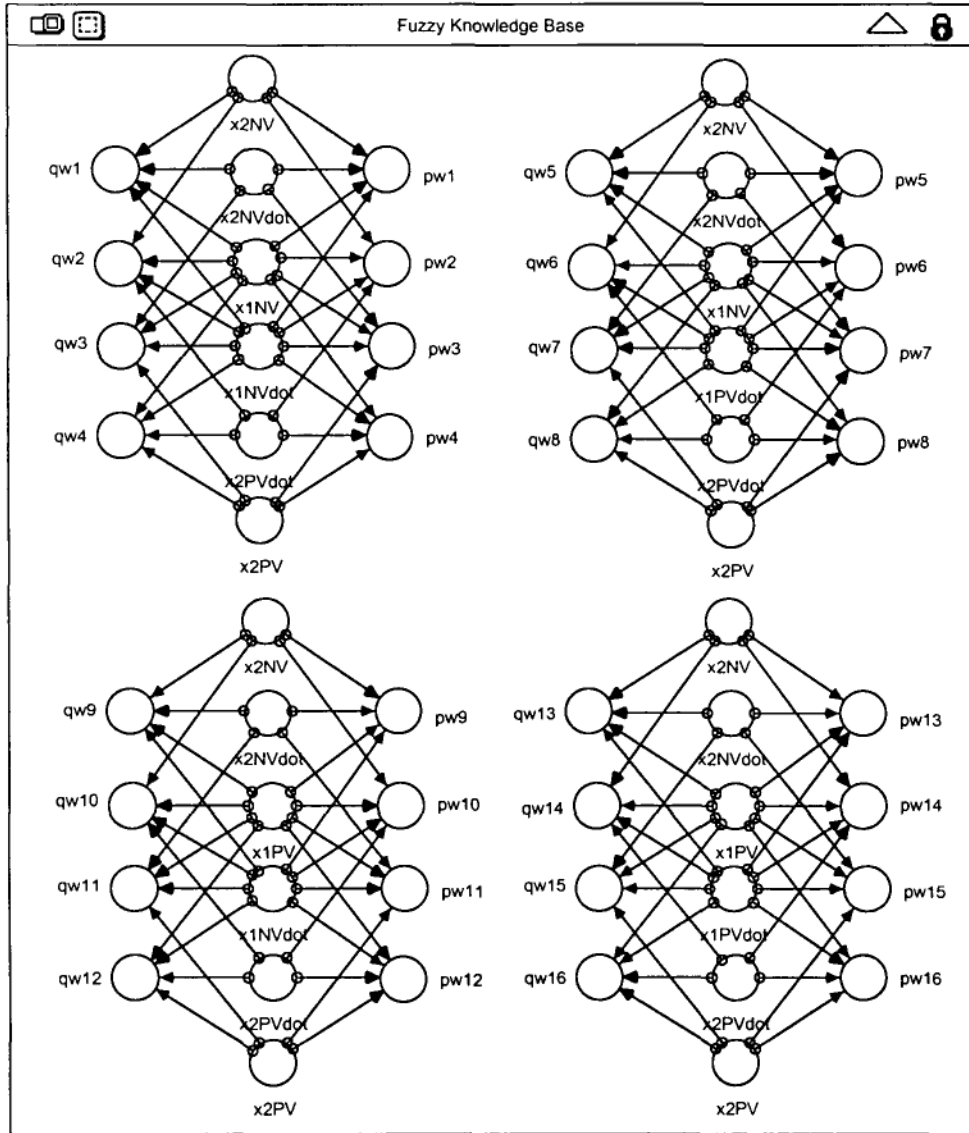


Figure 4-34: Fuzzy Knowledge Base using *ithink* software

The inference of the fuzzy rule system is carried out in Sector "Inference" that is shown in Figure 4-35.

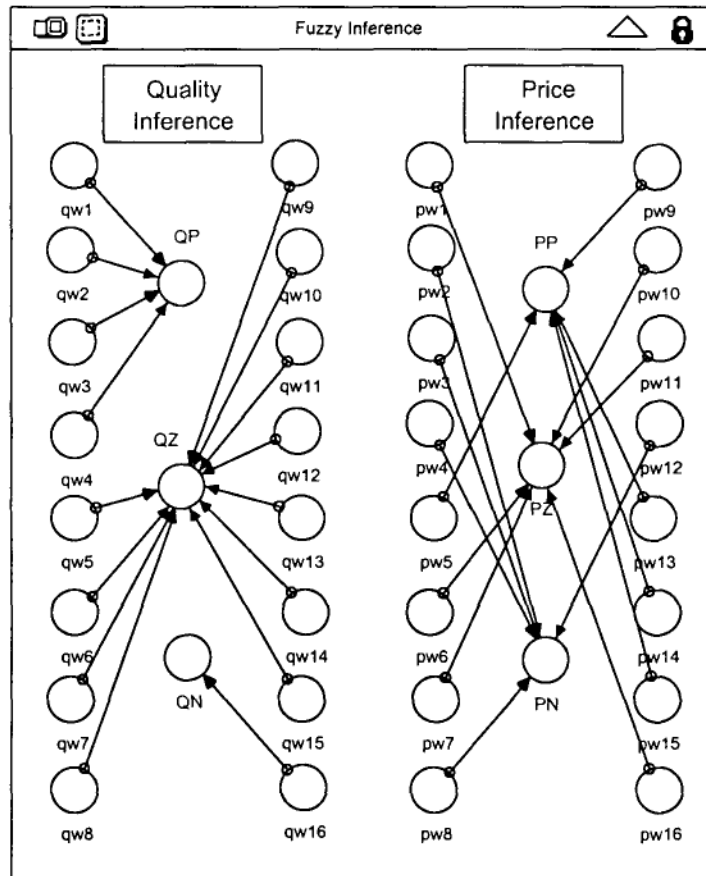


Figure 4-35: Fuzzy inference implementation using *itthink* software

The converters QN, QZ, and QP realize the *Max* operations to obtain the final conclusion for the output fuzzy variable *Increment in Hotel Service Quality*. In the same manner, the converters PN, PZ, and PP do the same for the fuzzy variable *Increment in Price*. For instance, the expression for QZ is:

$$QP = \max(qw1, qw2, qw3, qw4)$$

The last process is to convert fuzzy values to crisp values in the defuzzification process.

### Defuzzification

The Defuzzification process transforms fuzzy variables into crisp values. The crisp values in this case are the recommended decision of the virtual decision-maker for an increment in price or service quality.



Based on Mamdani's fuzzy model and the use of singletons as the output fuzzy sets, the Defuzzification process is simply a weighting sum. Sector "Defuzzification", which carries out this process, is shown in Figure 4-36.

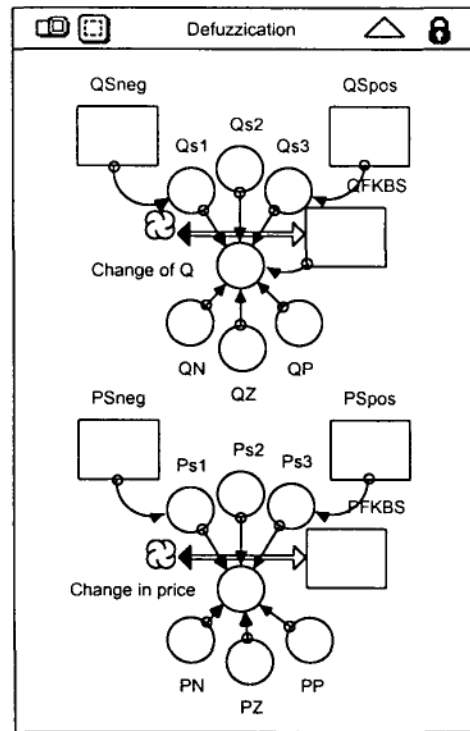


Figure 4-36: Defuzzification process implemented with *think* software

The crisp values are obtained in the Flows elements of Figure 4-36 named *Change in Price* and *Change in Quality*. If there is no change, for instance, in *Change in Price* then *PFKBS*, which is suggested Price from FKBS, remains the same. Otherwise, the recommended price by the FKBS changes. The same for *QFKBS* happens. It is relevant to note that the decision to make a change in price or quality is carried out in the Flow elements. In this way is also proved that all decisions are implemented in Flows.

$$\text{Change of } Q = \frac{QN * QS1 + QZ * QS2 + QP * QS3}{QN + QZ + QP}$$

$$\text{Change of } P = \frac{PN * PS1 + PZ * PS2 + PP * PS3}{PN + PZ + PP}$$

## 10. Testing the policies in the model and adjusting parameters.

### Testing Policies

The set of sixteen policies that form the FKBS is tested as a system with two objectives:

1. Increase Occupancy Percentage in 10% with regard to the last year
2. Increase Profits in 5% with respect to the last year

Both the test and the adjustment process are realized by the trial and error method. In this form, the method for eliciting and represent qualitative knowledge is also proved.

Rules and parameters are adjusted until the model behavior creates confidence to the participants. This is the criterion to take the model as valid. The constructed model is then considering a hypothesis that needs to be validated with the reality in following processes.

The initial set of policies was modified in rules 1, 2, 3 and 4 during the process of testing and adjustment. The rules refer to the situation where *Occupancy Percentage* is below the desired condition and there is a tendency to keep going down. The policies initially proposed that correct this situation was to increase the service quality ( $\Delta u_1$ ) and sustain the current price ( $\Delta u_2$ ). The situation and the actions are represented by:

Rule	$e_1$	$\Delta e_1$	$e_2$	$\Delta e_2$	$\Delta u_1$	$\Delta u_2$
1.	N	N	N	N	P	Z
2.	N	N	N	P	P	Z
3.	N	N	P	N	P	Z
4.	N	N	P	P	P	Z

However, the Virtual Decision-Maker was not able to rise the Occupancy Percentage. So, a change of policies was proposed to reduce the price in order to make the hotel attractive to the customers. The policies are represented by:

Rule	$e_1$	$\Delta e_1$	$e_2$	$\Delta e_2$	$\Delta u_1$	$\Delta u_2$
1.	N	N	N	N	P	N
2.	N	N	N	P	P	N
3.	N	N	P	N	P	N
4.	N	N	P	P	P	N

Rule one had to be adjusted again. This rule represents a very critical situation. It represents a condition where not only *Occupancy Percentage* is below the desired condition and has the tendency to keep going down, but also *Profits* is in the same condition at the same time. So, there is no margin to maneuver at all. For this case, an option that worked was to increase service quality and sustain current price. It is represented then as:

Rule	$e_1$	$\Delta e_1$	$e_2$	$\Delta e_2$	$\Delta u_1$	$\Delta u_2$
1.	N	N	N	N	P	Z

The final set of rules has been presented in Table 4-11 and in Figure 4-34 in the form of Fuzzy Knowledge Base.

### Adjusting Parameters

The parameters “ $a$ ” shown in Figure 4-29 were adjusted for the four input linguistic variables  $e_1$ ,  $\Delta e_1$ ,  $e_2$ , and  $\Delta e_2$ . Also the pair of singleton Negative and Positive shown in Figure 4-31 for the two-output linguistic variables  $\Delta u_1$  and  $\Delta u_2$  were adjusted.

The problem was then a parameter estimation problem. Find the value of “ $a$ ” for each of the four input linguistic variables and the two singleton values for each of the two output linguistic variables such that criteria  $J_1$  and  $J_2$ , and final values of the two deviation variables are as smallest as possible. In means, the process involves finding a set of 8 parameters under four criteria. The two criteria  $J_1$  and  $J_2$  are described below and are the effective values of the *Occupancy Percentage Deviation* ( $e_1$ ) and *Profit Deviation* ( $e_2$ ) signals.

$$J_1 = \sqrt{\frac{1}{T_h} \int e_1^2 dt} \quad \text{and} \quad J_2 = \sqrt{\frac{1}{T_h} \int e_2^2 dt}$$

Different methods could face the problem. From AI, genetic algorithms and simulated annealing might be two of them. However, in this case, the focus of the problem is not optimization but just finding a solution that works well enough and fit with the process of qualitative knowledge acquisition, proposed by this research.

Values of 10 and 5 for the different “ $a$ ”s were tried since the administration and business goals were to obtain increments of 10% and 5% on *Occupancy Percentage* and *Profits*, respectively. The total state space was then explored with fixed singleton values  $\pm 0.8$  and  $\pm 100$  for Negative and Positive *Increment in Price* and *Increment in Service Quality*, respectively.

**Table 4-12: Adjustment of parameters for linguistic variables**

Test number	$a$ for $e_1$	$a$ for $\Delta e_1$	$a$ for $e_2$	$a$ for $\Delta e_2$	$J_1$	$J_2$	Final Occupancy % deviation	Final Profit % deviation
1.	5	5	5	5	2.2	1.7	1.0	-2.4
2.	5	5	5	10	2.3	1.7	0.4	-2.3
3.	5	5	10	5	2.3	1.8	5.5	-4.5
4.	5	5	10	10	2.4	1.9	5.4	-4.5
5.	5	10	5	5	2.2	1.7	-3.0	-2.0
6.	5	10	5	10	2.2	1.8	-3.5	-1.9
7.	5	10	10	5	2.1	1.9	0.2	-4.9
8.	5	10	10	10	2.2	1.9	0.3	-5.0
9.	10	5	5	5	1.9	1.7	-0.9	-2.0
10.	10	5	5	10	1.9	1.7	-2.1	-1.8
11.	10	5	10	5	1.9	1.8	3.6	-4.2
12.	10	5	10	10	2.0	1.9	3.6	-4.3
13.	10	10	5	5	2.0	1.7	-5.3	-1.3
14.	10	10	5	10	2.0	1.8	-5.5	-1.4
15.	10	10	10	5	-1.8	1.8	-2.7	-4.1
16.	10	10	10	10	1.9	1.9	-3.2	-4.2

The singleton values were proposed assuming a 0.8 increment in *Service Quality* and \$100.00 in *Base Price* as strong change in a frequency of increment/month. *Service Quality* values range from 1 to 5. *Base Price* values range from \$800.00 to \$1600.00 in a frequency of increment/month. The result of the process is showed in Table 4-12.

Selected values for “ $a$ ”s appear in set number 10. It can be observed that no set was able to achieve the four criteria at the same time. The best  $J_1$  is obtained by set number 15. Criterion  $J_2$  is obtained by sets 1, 2, 5, 10, and 13. Smallest final values of *Occupancy Deviation* and *Profit*

*Deviation* are obtained by sets 7 and 13. Set number 10 completely satisfied  $J_2$  and partially the others taking into account a good balance among the others indicators. It should say that *Profits* received more attention since the problematic situation of the hotel is the low level of profits. Final values are declared in Tables 4-9 and 4-10 for the input and output variables, respectively.

Simulation results y discussion is presented in Section 4.4.

#### 4.4.3 Step 3 Utilization of the Policies in Computational Models to Respond and Generate New Questions

This step was not experimentally carried out with human participants. The reason is machine learning and not human learning is what Artificial Intelligence is more interested about. Human learning was suggested to stay out of the focus for this research. In next section 4.3, it is then presented the Adaptive Mechanism incorporated to the Virtual Decision-Maker along with the simulation results.

The human interface man-machine of the simulator model that should be used to carry out the Step 3 with human participants is presented in Figure 4-37.

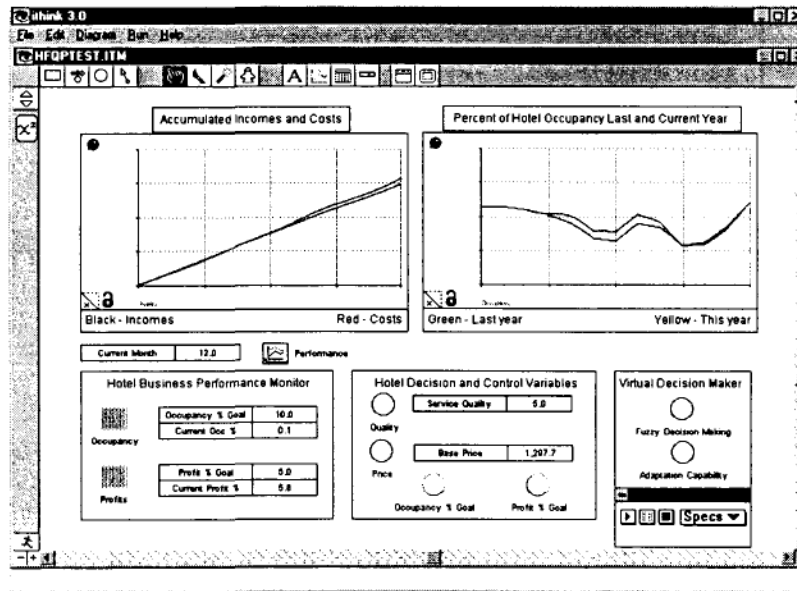


Figure 4-37: Interface human-machine of the simulation model

The panel of interface human machine is designed to expose and receive information to and from the participating decision-makers. It is divided in five sections. (1) Tendency graph of accumulated incomes and costs, graph located at left top corner. This section allows to perceiving

explicitly the moment when the financial equilibrium point is reached. (2) Tendency graph for occupancy percentage is located at the right top corner. This graph allows to visually comparing current and last year occupancy percentage of the hotel. (3) Section “Hotel Performance Monitor” presents information in numerical mode about the current and desired conditions of Profits and Occupancy Percentage. (4) Section “Hotel Decision and Control Variables” has the function of acquiring and showing the values of Service Quality and Base Price currently offered. (5) Section “Virtual decision-Maker” allows to turning on/off both the virtual decision-maker and its adaptive mechanism. Below this section, the run/stop box appears.

Step 3 should be worked with the following sequence:

1. Challenge the participants to drive the business in the computer.
2. Ask the participants for observing how the virtual decision-maker performs in the same task. Allow them to periodically discuss the events enabling pauses during the simulation.
3. Compare the performance of the participants and the virtual decision-maker. Make to note the fact that he or she is competing against his or her own knowledge.
4. Adjust policies in the knowledge-based fuzzy system.
5. Let the participants execute as many times as they desire Step 3 in order to allow them to adjust their own policies through active discussions. The focus of Step 3 is to facilitate learning among the participants, making reflections of their own actions.

## 4.5 Adaptive Mechanism

The Adaptive Mechanism is applied to automatically adjust the singleton values of the Fuzzy Decision-Maker’s output variables based on previous performance. Fuzzy membership parameters are fixed at previously selected values.

The idea of the mechanism was adopted from (Haissig, 2000) who patented for Honeywell the idea for controlling hydronic heating systems. The original idea was applied to a single input – single output system with five membership functions for the reference (goal), three membership functions for temperature deviation, seven singletons and fifteen rules.

The difference with the present implementation is the application to a MIMO system (2 x 2) with two membership functions each of the four input linguistic variables, three singletons (one is fixed) each of the two output linguistic variables and sixteen rules.

The implementation of Sector “Adaptive Mechanism” using *ithink* is shown in Figure 4-54. The four singletons have been implemented in the level variables *Qsneg*, *Qspos*, *Psneg*, and *Pspos* shown in the Figure 4-38.

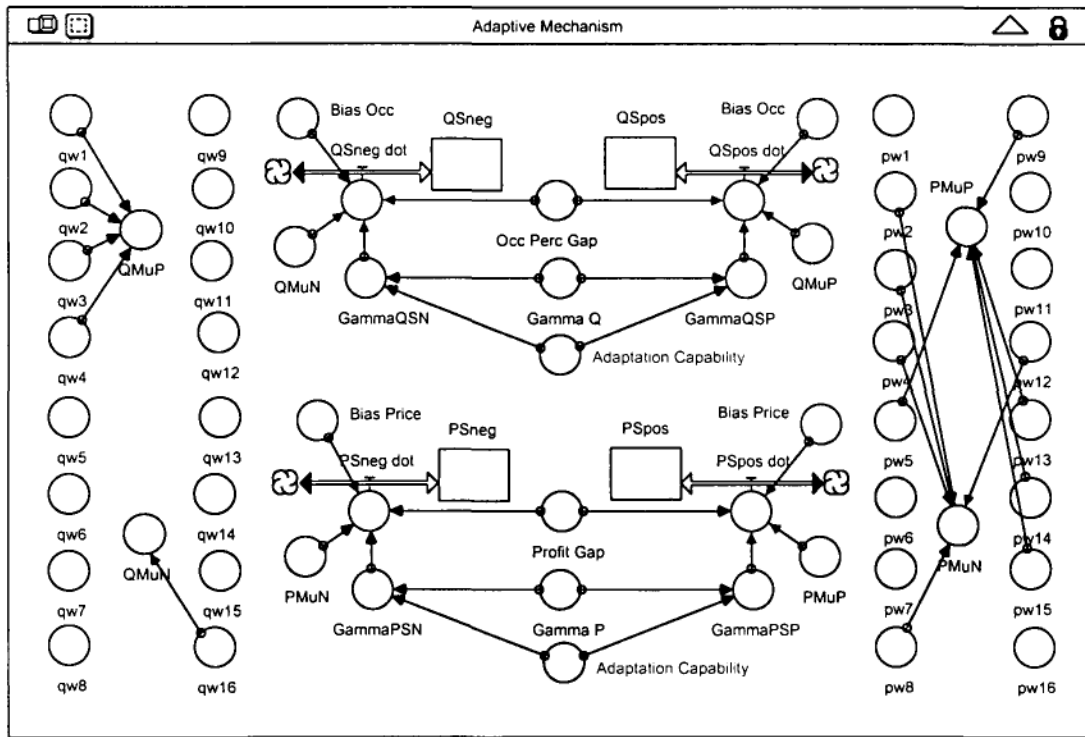


Figure 4.38: Implementation of the adaptive mechanism

The adaptive mechanism automatically locates the singletons of the system based on the use of the Fuzzy Knowledge Base (FKB). Indeed, the mechanism is the application of a similar delta rule equation from MIT in model reference adaptive control (Åstrom and Wittenmark, 1995, cited by Heissig, 2000) and the least-mean-squares rule in fuzzy modeling (Yager and Filev, 1994, cited by Heissig, 2000).

The mathematical expression for the four singletons in adaptation is:

$$\frac{d}{dt}Ur_{ule} = \begin{cases} \gamma\mu_{rule}e & \text{for } |e| > bias_{error} \\ 0 & \text{for } |e| \leq bias_{error} \end{cases} \quad (\text{note}^9)$$

where *Ur<sub>ule</sub>* refers to singleton value; *e* is the deviation between desired and current condition;  $\mu_{rule}$  is the degree of membership function for a given rule, in our case it is the mean of the

<sup>9</sup> Equation (2) page 42 in (Heissig, 2000).

membership function that fires to a specific singleton;  $\gamma$  is the adaptation rate, and  $bias_{error}$  is the size of a dead band around the value of  $e = 0$ .

The expression refers to a rate of change of a singleton value based on the importance of its corresponding fired rule. The importance value is given by  $\mu_{rule}$ . The size and direction to adjust the singleton value is given by  $e$ , and the speed of adaptation is given by  $\gamma$ .

In this particular design,  $\mu_{rule}$  is computed by the mean of the membership functions of the associated firing rules. Relationship among rules and singletons are presented in Table 4-11. The implanted equations for Negative and Positive singletons of *Increment in Service Quality* and *Increment in Price* are the following:

$$\mu_{QualityService}^{Negative} = Mean(qw16)$$

$$\mu_{QualityService}^{Positive} = Mean(qw1, qw2, qw3, qw4)$$

$$\mu_{Price}^{Negative} = Mean(pw2, pw3, pw4, pw8, pw12)$$

$$\mu_{Price}^{Positive} = Mean(p5, pw9, pw13, pw14, pw15)$$

where  $qwi$  and  $pwi$  are the *Increment in Service Quality* and *Increment in Price* conclusions of the  $i$ -th rule.

The parameter values for  $\gamma$  and  $bias_{error}$  were found by trial and error method using same four indicators as they were used for determining the parameters of the membership functions in Section 4.2.2 - Subsection *Adjusting Parameters*. For sake of simplicity in the method, same  $\gamma$  and  $bias_{error}$  are applied to Negative and Positive singletons of each output linguistic variable. These values are shown in Table 4-13.

**Table 4-13: Parameter values for the Adaptive Mechanism**

Negative and Positive Singletons	$\gamma$	$bias_{error}$
<i>Increment in Quality Service</i>	0.02	2
<i>Increment in Price</i>	1.00	2

Simulation results are shown in Section 4.6.



## 4.6 Simulation Results

Simulation results are organized and discussed into three groups: (1) results without adaptive mechanism, (2) results with adaptive mechanism, and (3) results under influences of exogenous and special events. The goals are to make *Profits* 5% higher and *Occupancy Percentage* 10% higher than those obtained last years in the following twelve months.

### 4.6.1 Results without adaptive mechanism

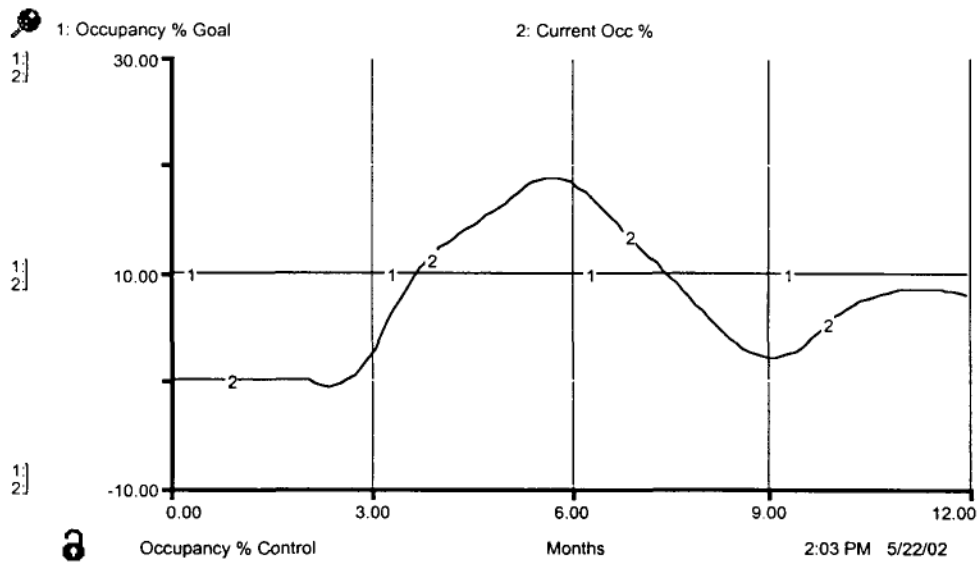


Figure 4-39: Desired and current occupancy % (parameter set 10)

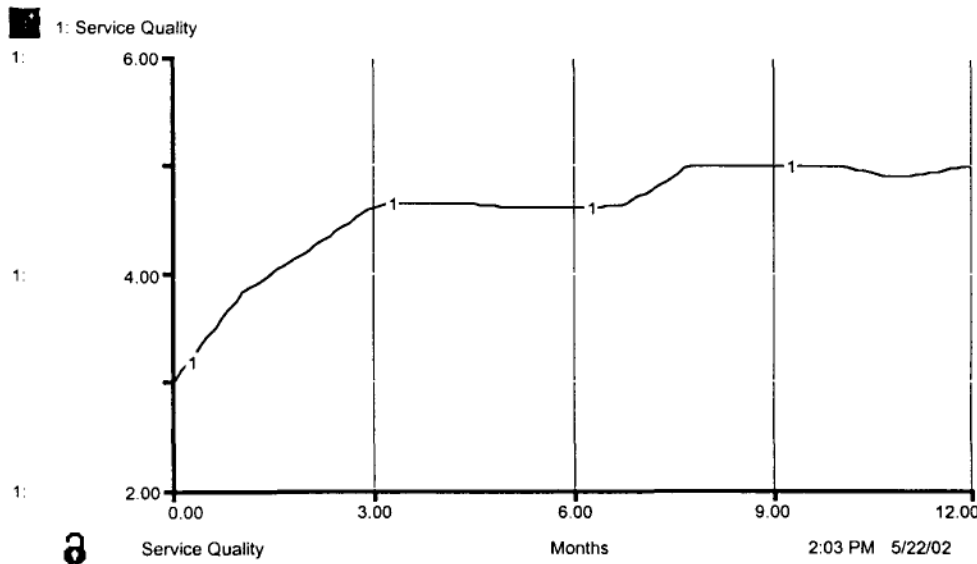


Figure 4-40: Actions in service quality (parameter set 10)

An increment of 10% in *Occupancy Percentage* has been established as a goal this year, and 5 % for *Profits*. The behaviors produced by parameters of set number 10 from Table 4-12 are shown in Figures 4-39 to 4-46. Desired and current state for *Occupancy Percentage* is shown in Figures 4-39. The driving variable *Quality Service* appears in Figure 4-40. It is observed an oscillatory behavior on *Occupancy Percentage* with an overshoot of 8% of *Occupancy Percentage* above the goal among the months five to seven.

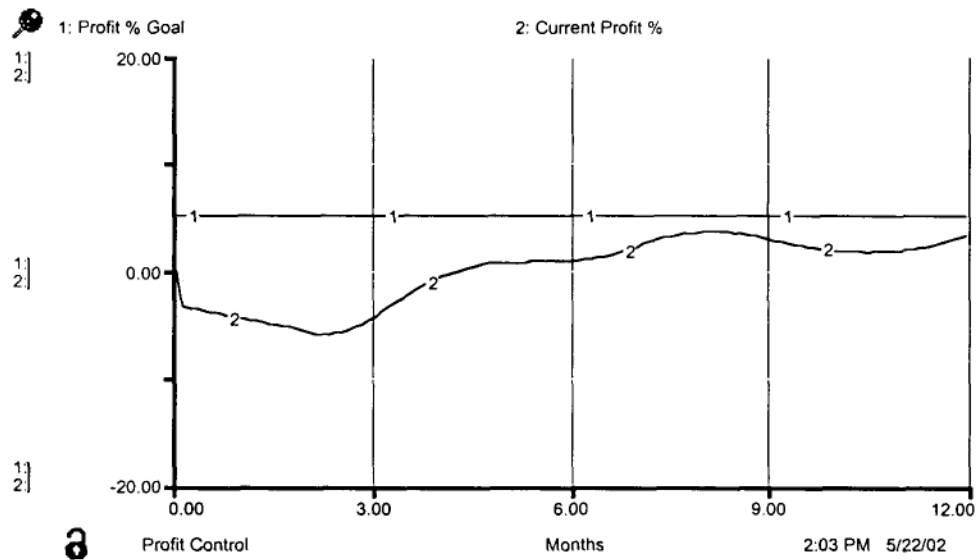


Figure 4-41: Desired and current profit % (parameter set 10)

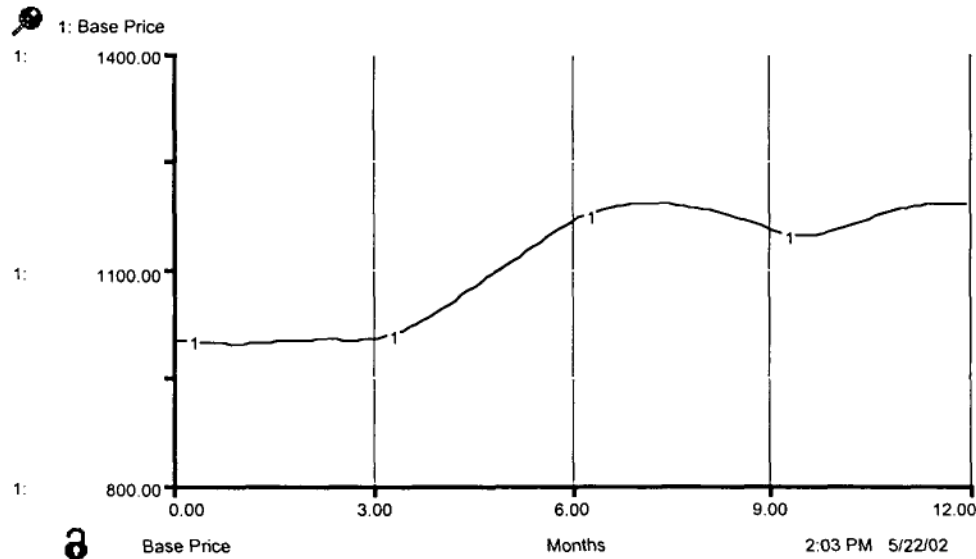


Figure 4-42: Actions in base price (parameter set 10)

The desired and current states for *Profit* are shown in Figures 4-41 and the driving variable *Base Price*, in Figure 4-42.

It can be observed that the Virtual Decision-Maker firstly increment the *Quality Service* without significantly varying the *Base Price* during the first three months. Then, it begins with slow increments in *Base Price*, maintaining the *Service Quality* constant –months between 3 and 6. By month 7, the increment in *Base Price* continues but now *Service Quality* is waiting for a condition to be increased again, which happens at the end of the month 7. *Service Quality* reaches the limit around month 8 and the *Base Price* is used as unique control variable. At month 9, *Base Price* decreases in order to rise the *Occupancy Percentage*, which is got it, but *Profits* decreases. Finally, *Service Quality* is then decreased to help current *Profit*. At the end, steady state is not reached in one year. Stability can be inferred by looking at the information of deviation signals in their phase plane plots, Figures 4-44 and 4-45.

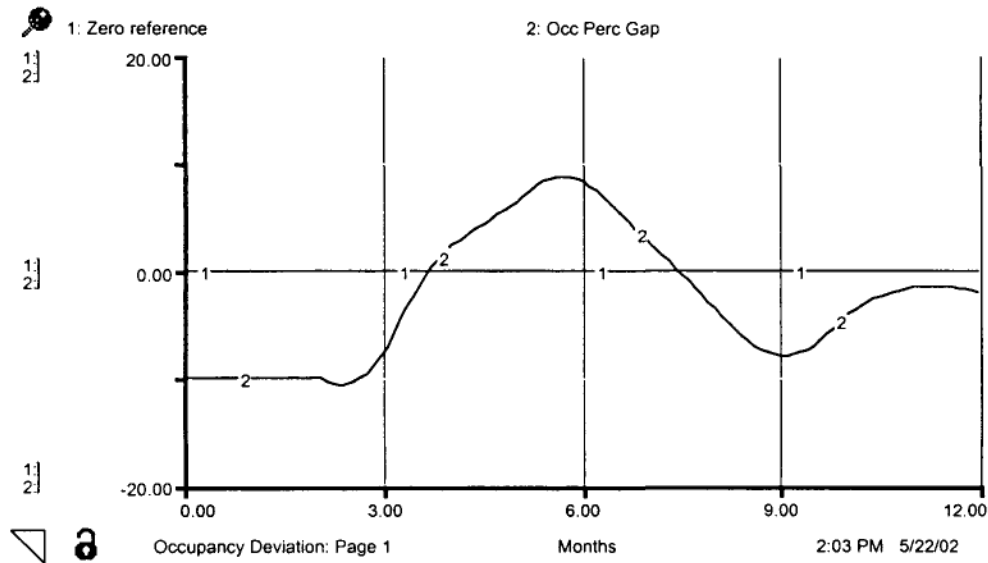


Figure 4-43: Occupancy % deviation (parameter set 10)



Figure 4-44: Phase plane for occupancy % deviation (parameter set 10)

It can be observed how both deviations signals are driven toward their origins, their designed attractors: (10,0) for *Occupancy Percentage*, and (5,0) for *Profits* in their respectively phase planes. The deviation signals of *Occupancy Percentage* and *Profits* trough time are shown in Figures 4-43 and 4-45. Observe the forms, which are the same as Figure 4-39 and 4-41 respectively, without the offset given by the goals. This is why the deviation signals are taken for designing the decision-maker. They contain the required information to make decisions.

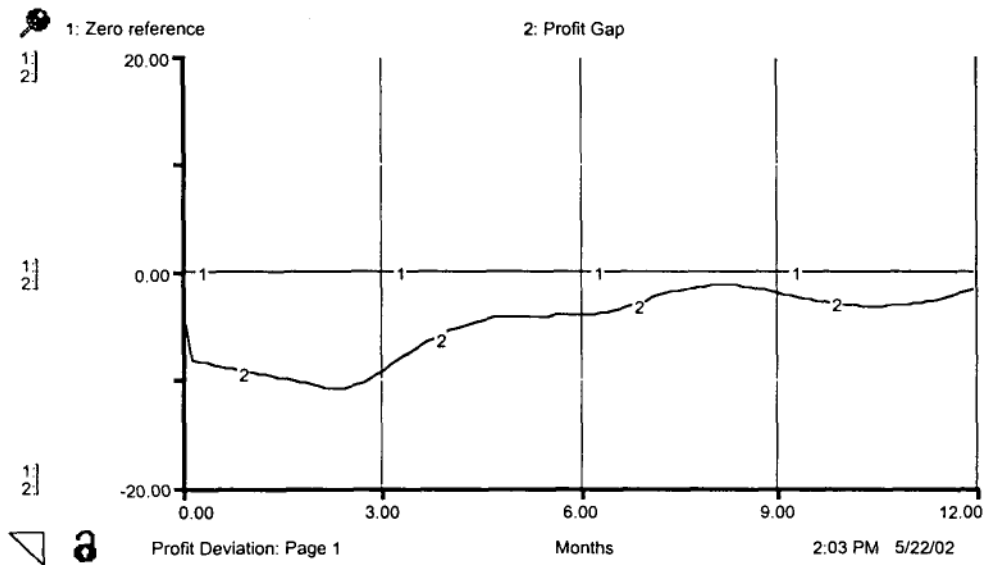


Figure 4-45: Profit % deviation (parameter set 10)

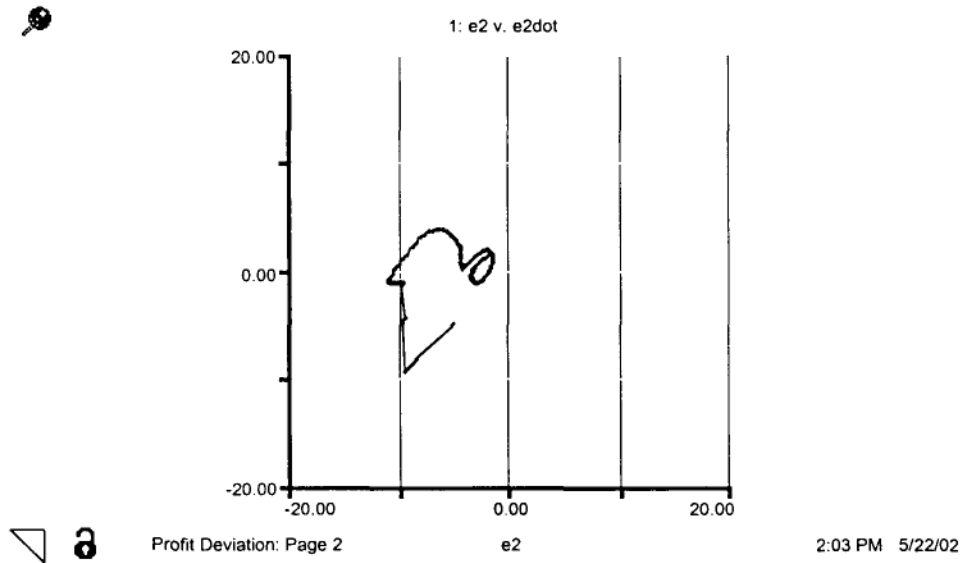


Figure 4-46: Phase plane for profit deviation (parameter set 10)

Results with set number 13 are shown for comparison in Figures 4-47 to 4-54. A better behavior on *Profits* and worse on *Occupancy Percentage* than that produced by set number 10 is observed.

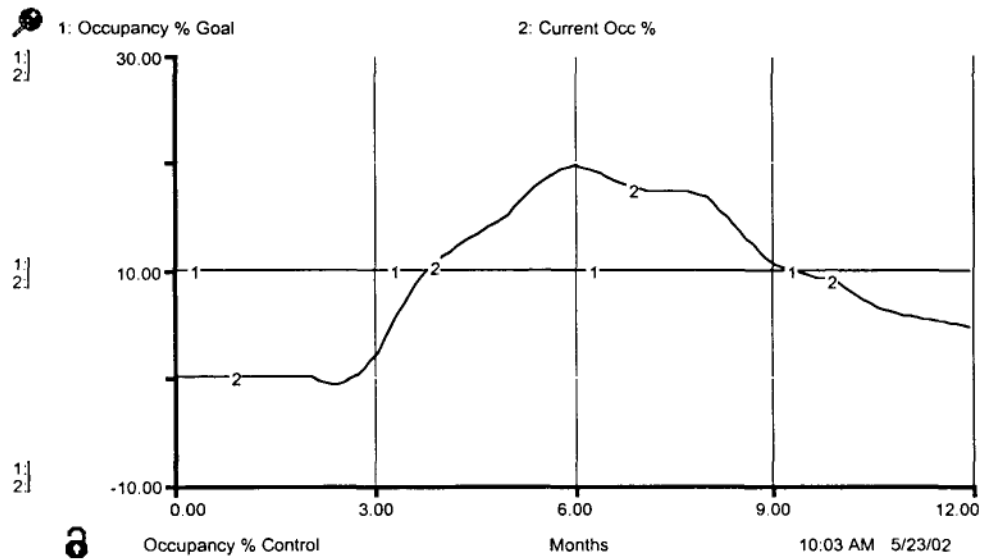


Figure 4-47: Desired and current occupancy % (parameter set 13)

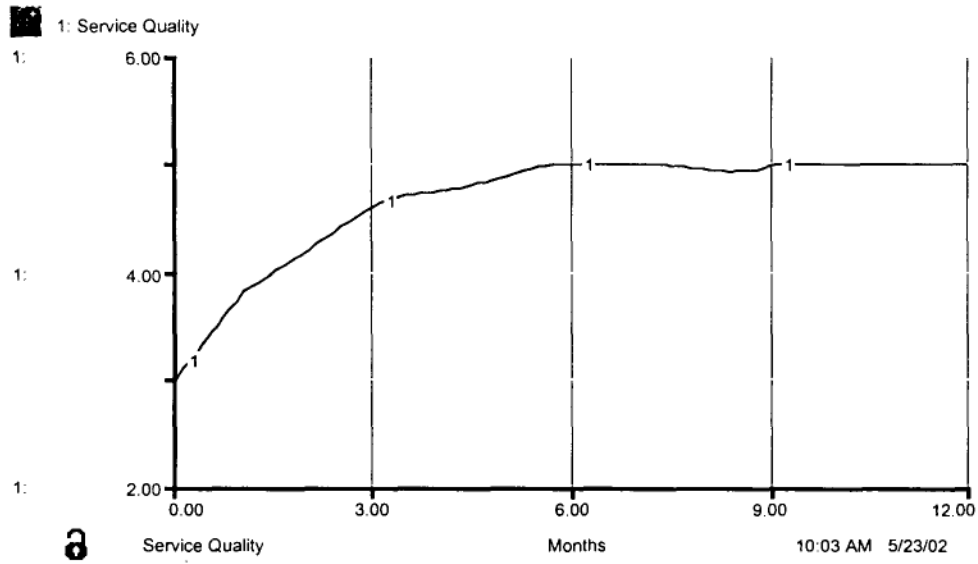


Figure 4-48: Actions in service quality (parameter set 13)

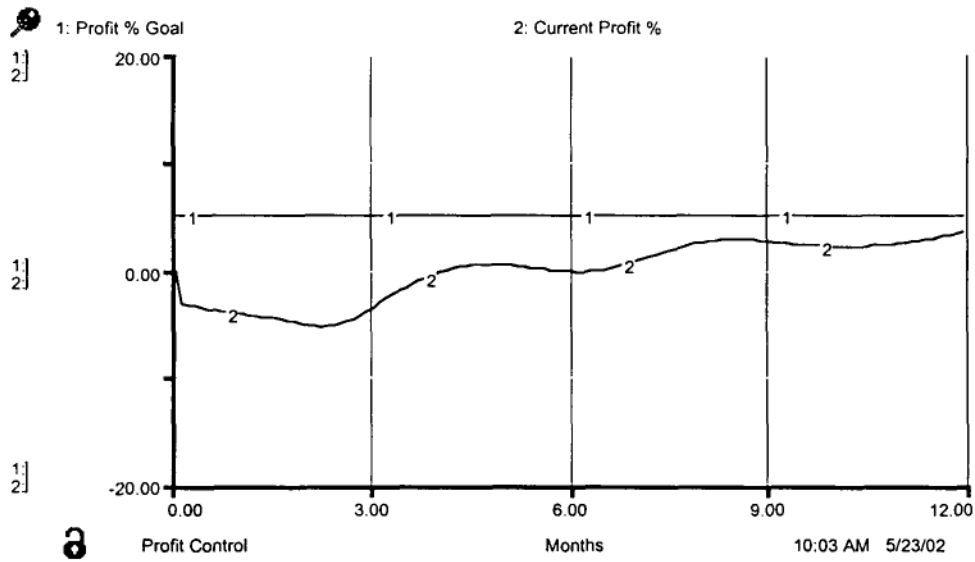


Figure 4-49: Desired and current profit % (parameter set 13)

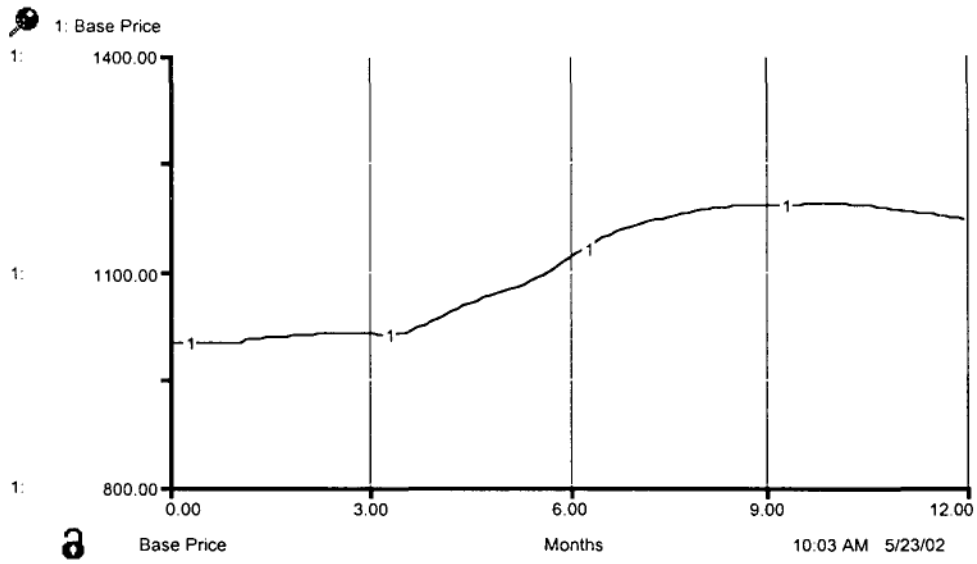


Figure 4-50: Actions in base price (parameter set 13)

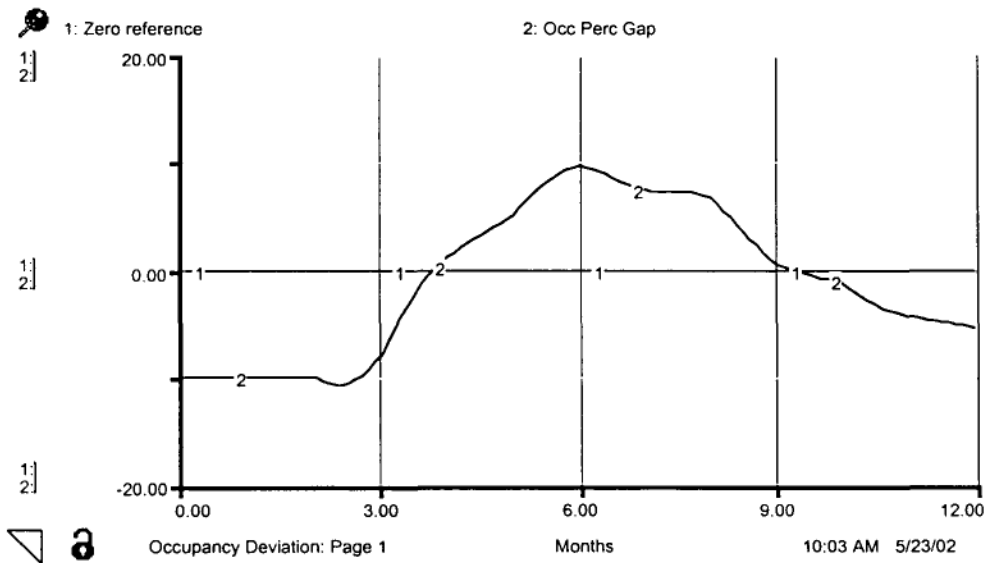


Figure 4-51: Occupancy % deviation (parameter set 13)

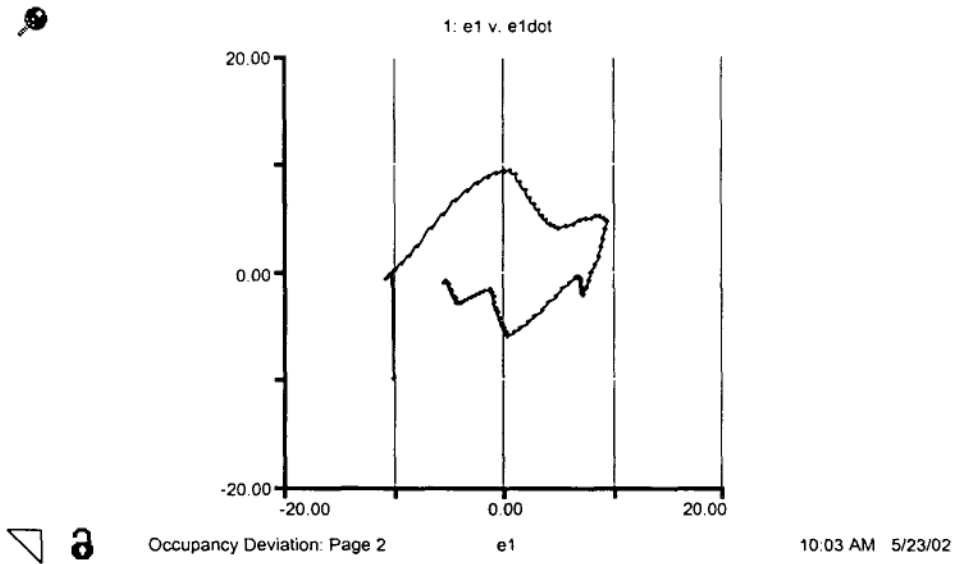


Figure 4-52: Phase plane for occupancy % deviation (parameter set 13)

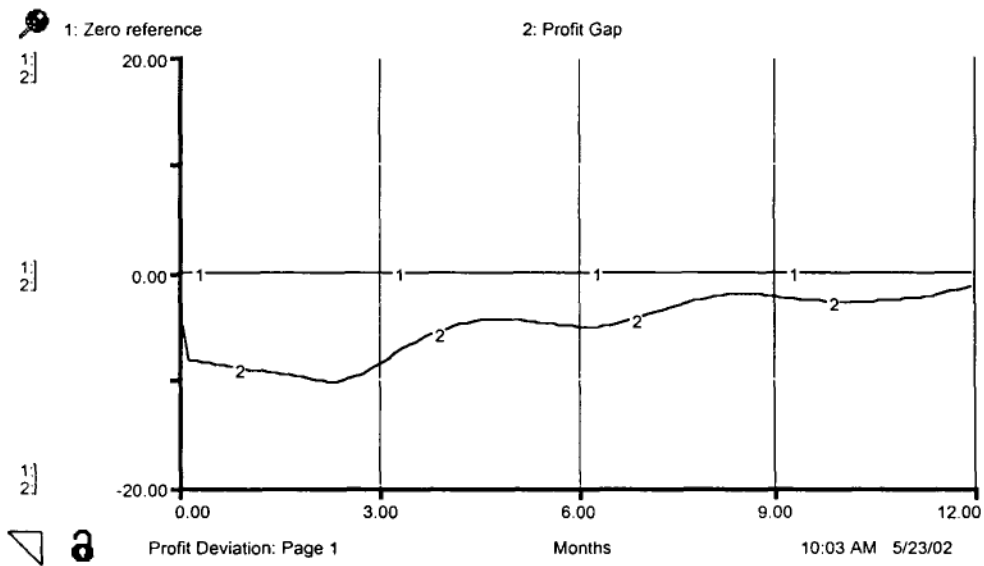


Figure 4-53: Profit % deviation (parameter set 13)



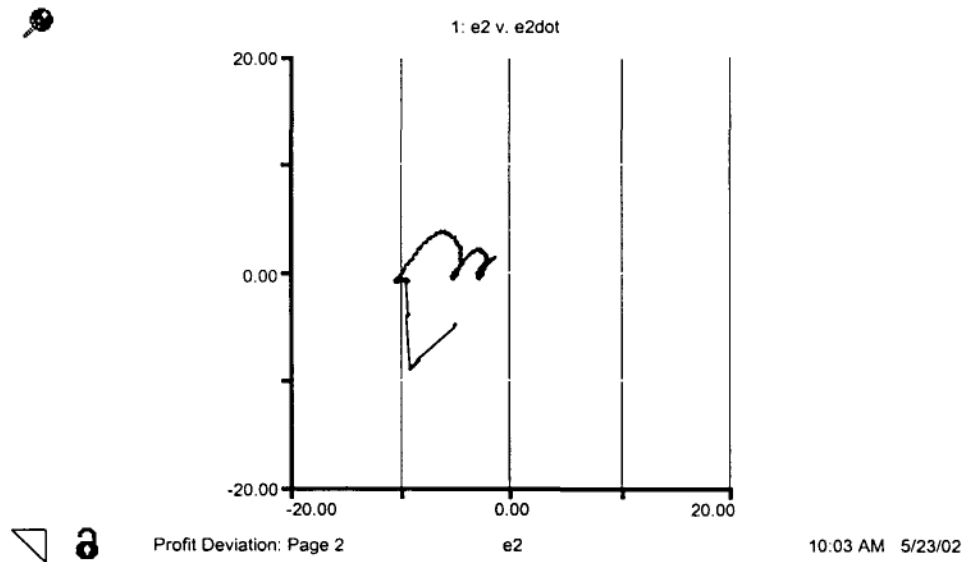


Figure 4-54: Phase plane for profit deviation (parameter set 13)

The model is valid for a 12-month time period. After that year if the demand remains constant for two years, the Occupancy Percentage goal is reached and sustained with an oscillating behavior of +3% amplitude over the goal. The Profit goal is surpassed and sustained at 35% over the goal. However, the model can not be considered valid anymore.

### 4.6.2 Results With Adaptive Mechanism

The best-obtained behaviors with the adaptive mechanism of the system are shown in Figure 4-55 to 4-64. It can be observed improvement in *Occupancy Percentage* but deterioration in *Profit*. This is clearly observed in the indicators shown in Table 4-14.

Table 4-14: Comparison of performance indicators with and without Adaptive Mechanism

	$J_1$	$J_2$	Final Occupancy % deviation	Final Profit % deviation
With Adaptation	1.7	1.8	0.0	-2.9
Without Adaptation	1.9	1.7	-2.1	-1.8

It should be clear at this moment that this research is not a control problem but a qualitative knowledge acquisition problem and it is not oriented to get an optimum performance of the

adaptive mechanism. The non-linear and highly coupled hotel business process (HBP) with the imposed goals might be a good challenge for more sophisticated control algorithms.

For the purposes of this research, the HBP and the FKBS working in close loop demonstrate the method is effective to realize qualitative knowledge acquisition. The adaptive mechanism allows to eliciting more information from the participants by perceiving how the system on its own tries to improve its performance. This provides special environments for more discussion for discussion among participants and making explicit more of their tacit and qualitative knowledge.

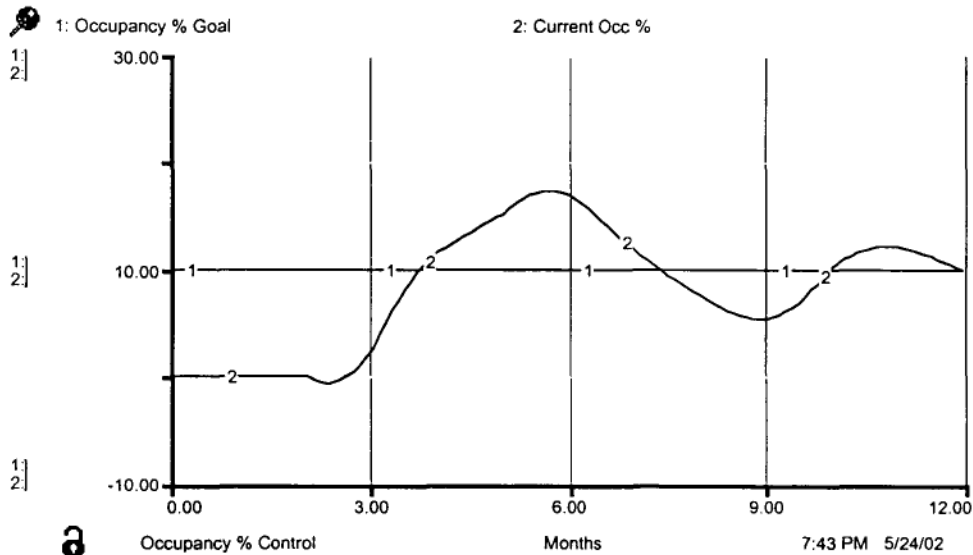


Figure 4-55: Desired and current occupancy % (with adaptation)

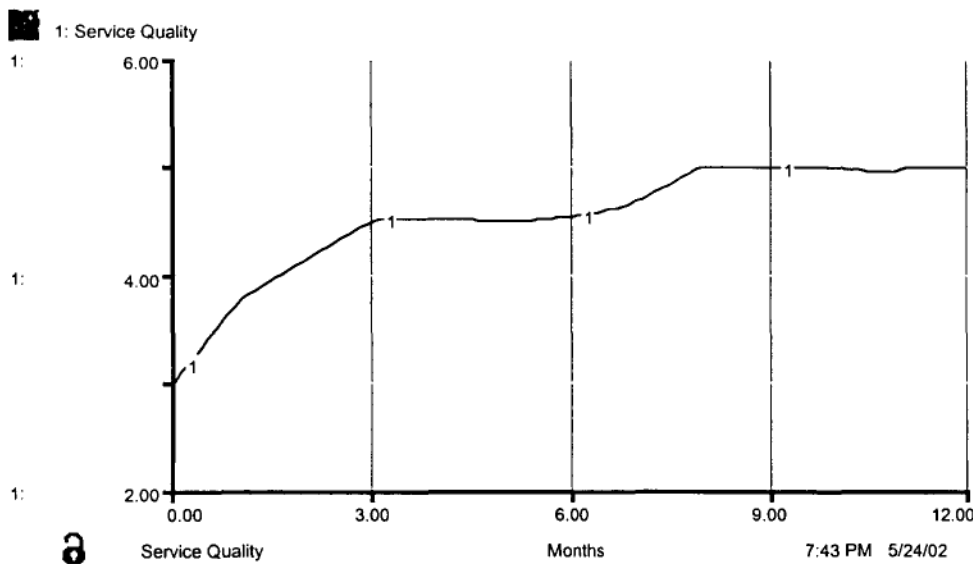


Figure 4-56: Action in service quality (with adaptation)

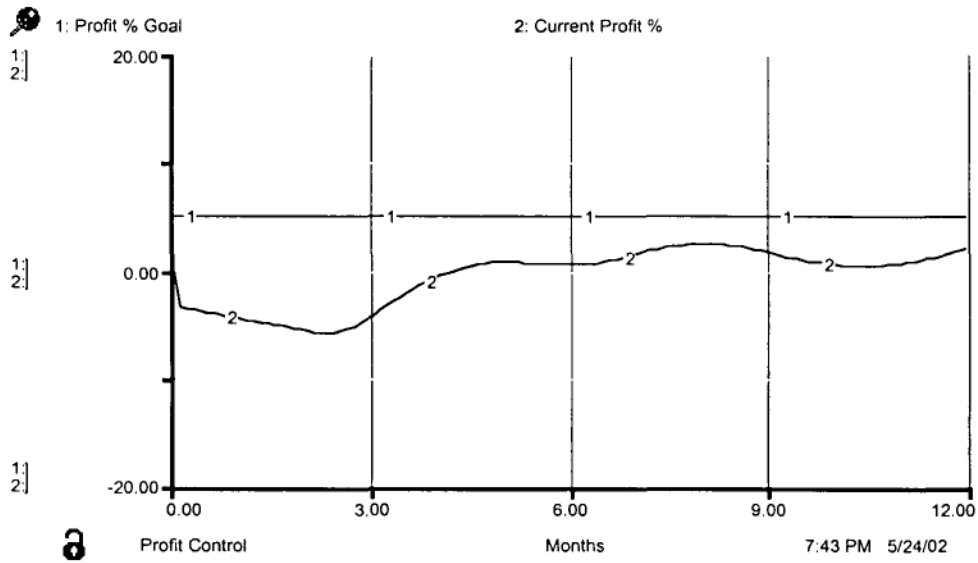


Figure 4-57: Desired and current profit % (with adaptation)

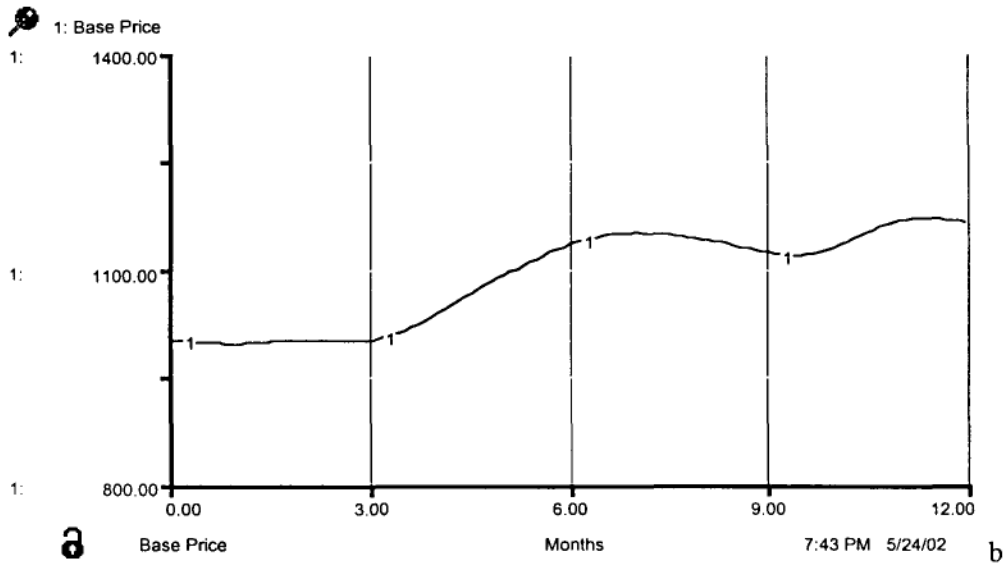


Figure 4-58: Action in price (with adaptation)

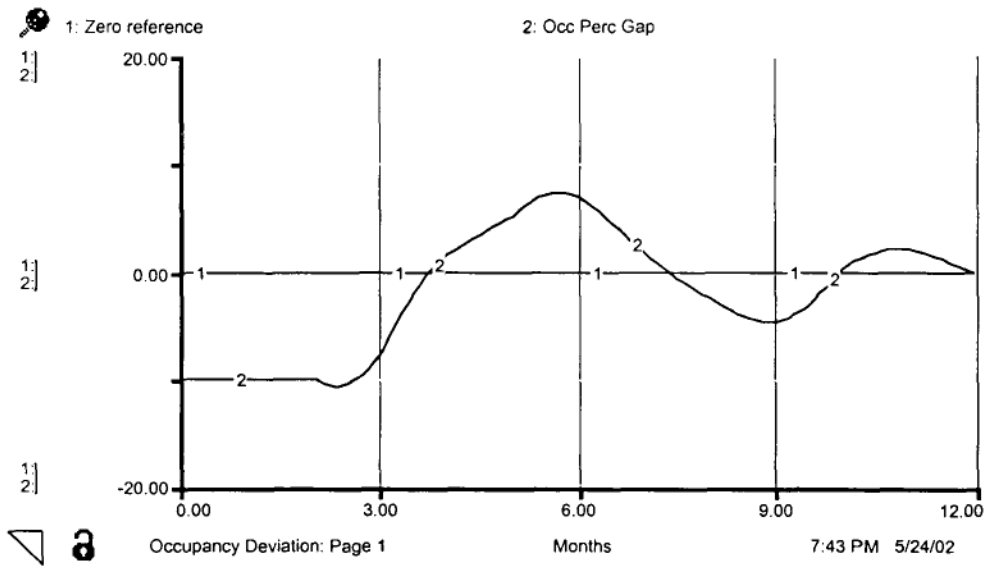


Figure 4-59: Occupancy % deviation (with adaptation)

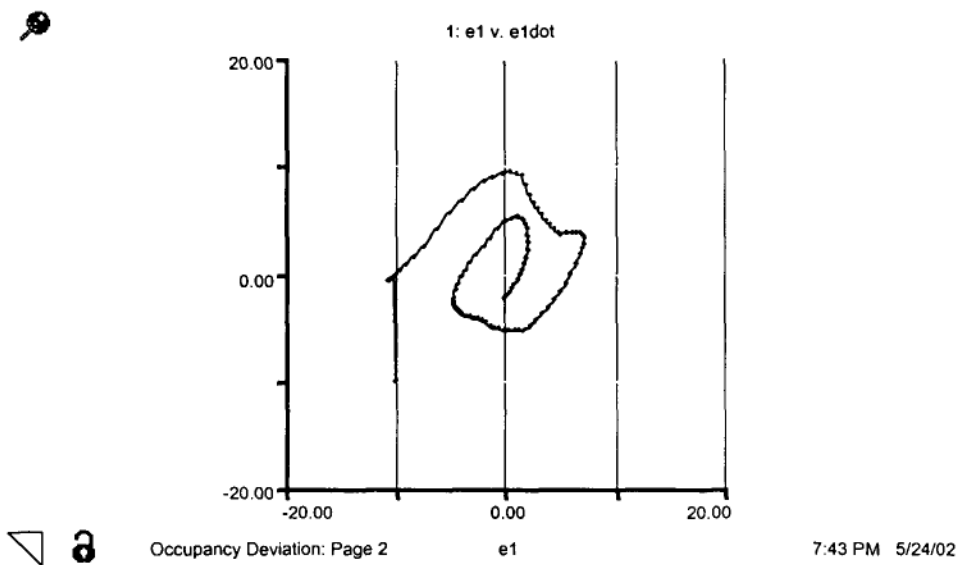


Figure 4-60: Phase plane for occupancy % deviation (with adaptation)

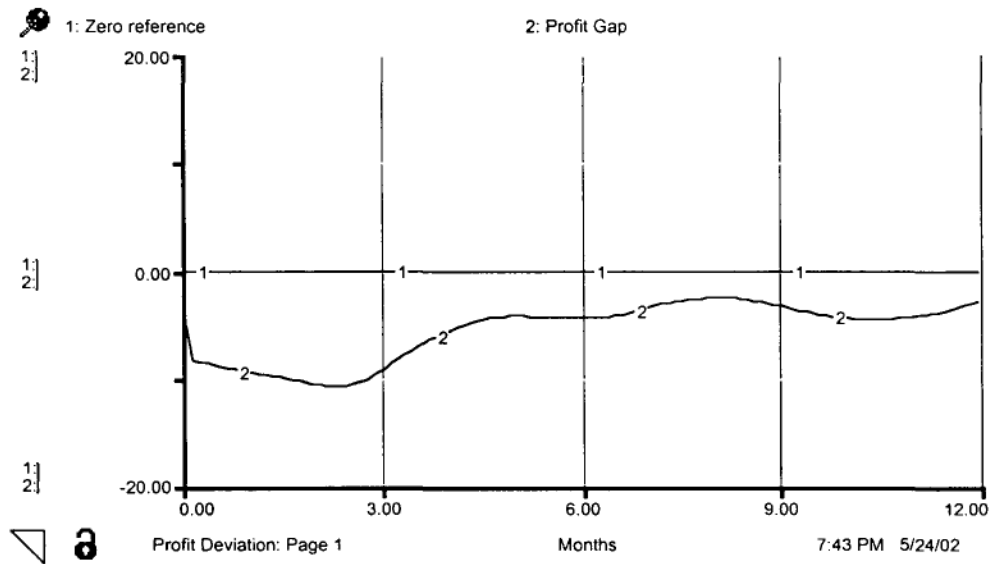


Figure 4-61: Profit % deviation (with adaptation)

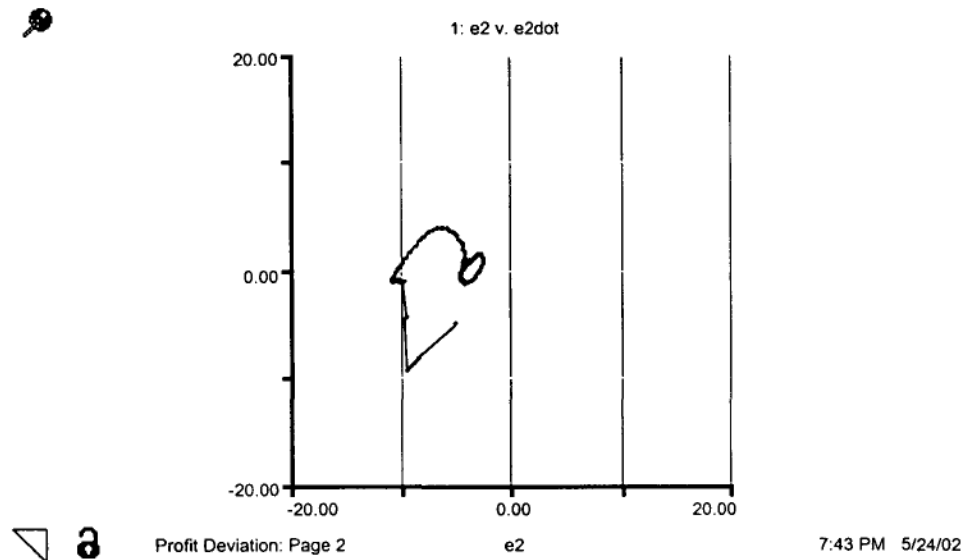


Figure 4-62: Phase plane for profit deviation (with adaptation)

The changes of the singleton values, caused by the adaptive mechanism, through the time are shown in Figures 4-63 and 4-64. Negative and positive singletons for *Increment in Service Quality* are labeled QSneg and QSpos, respectively in Figure 4-63. Same for *Increment in Price*, whose singletons are labeled PSneg and PSpos in Figure 4-64.

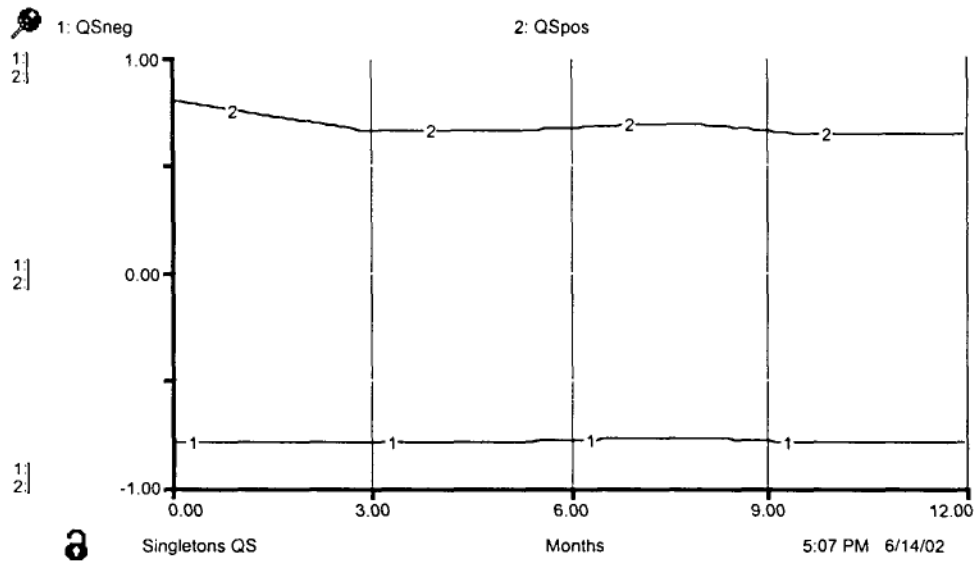


Figure 4-63: Dynamics of singletons corresponding to Increment in Quality Service

It can be observed convergence of singletons QSneg and QSpos to a finite value. However, not the same for PSneg and PSpos, which both are in slight movement but with a slow dynamic. With this behavior, the stability of the system in close loop can be guaranteed for the specific time horizon of 12 months, which is the time period of interest.

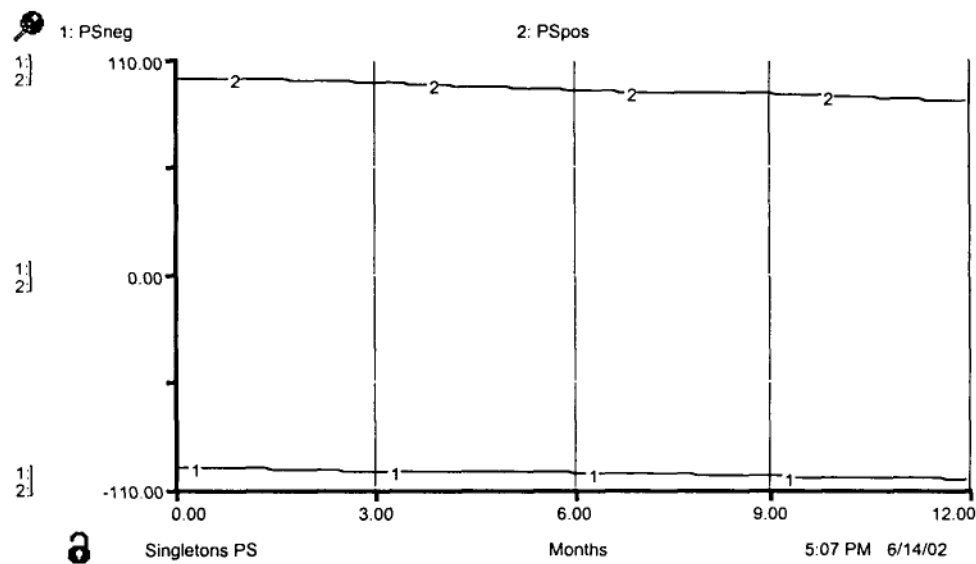


Figure 4-64: Dynamics of singletons corresponding to Increment in Price

Conclusions and comments along with recommendations for future research are presented in the next section.

### 4.6.3 Results Under Influences of Exogenous and Special Events

An exogenous event was included in the model. This event could represent a change of policy of the government, a devaluation situation, a hurricane, it is just an anticipated event that is present in some moment. The event was programmed to appear in the sixth month of the simulation.

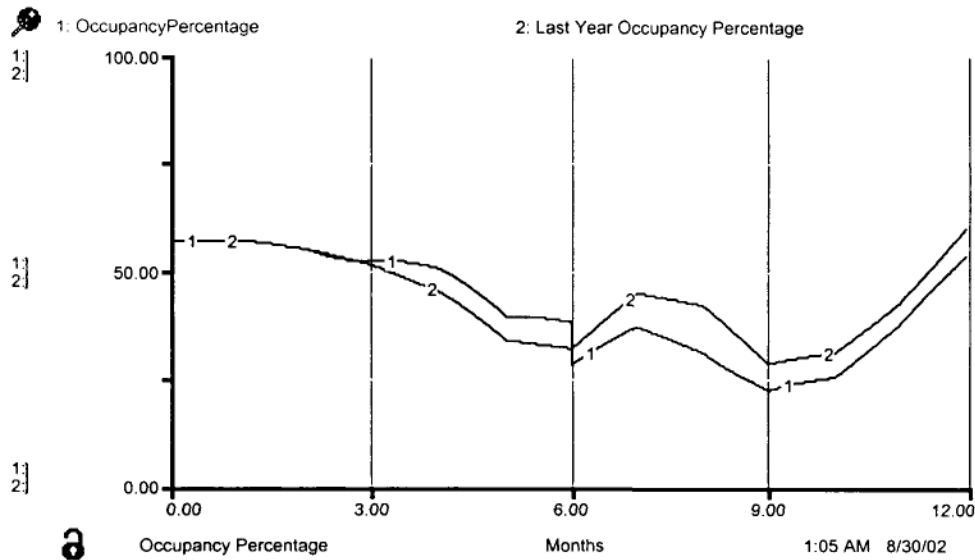


Figure 4-65: Comparative Occupancy percentage from current and last years

In Figure 4-65, line 1 is the pattern of behavior of clients in the current year and line 2, in the past year. In Figure 4-66, the resulting equilibrium point is observed on the month six.

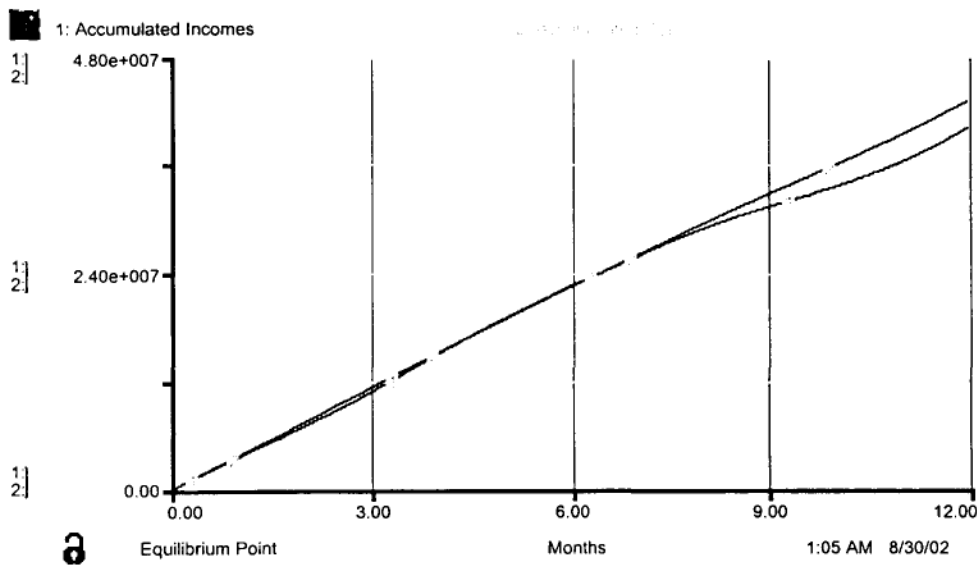


Figure 4-66: Equilibrium Point from Accumulated Incomes and Costs

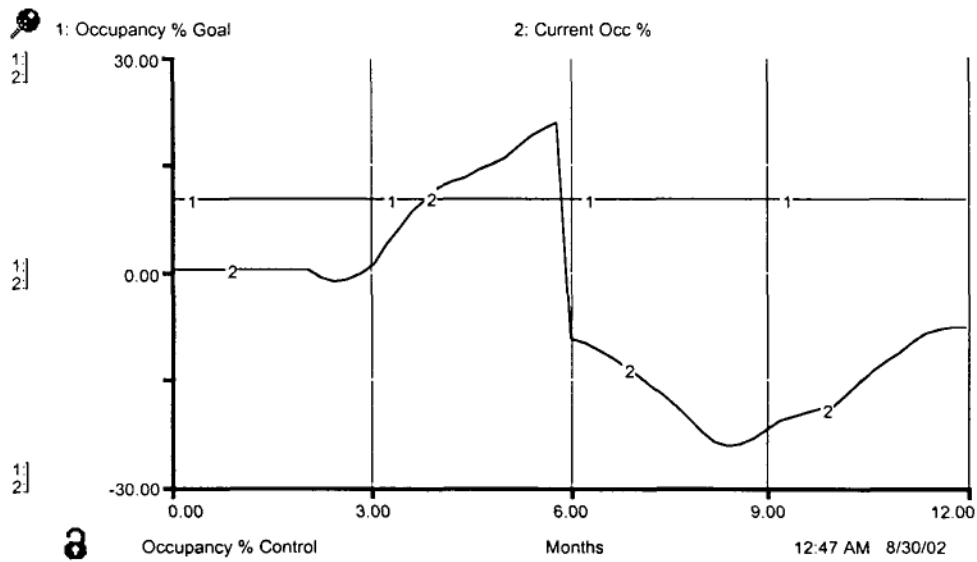


Figure 4-67: Desired and current occupancy %

The change that occurred was so unexpected that the system will not recover in the next 6 months. Below, it can be observed the driving variable of *Quality Service* being pushed at the top stars.

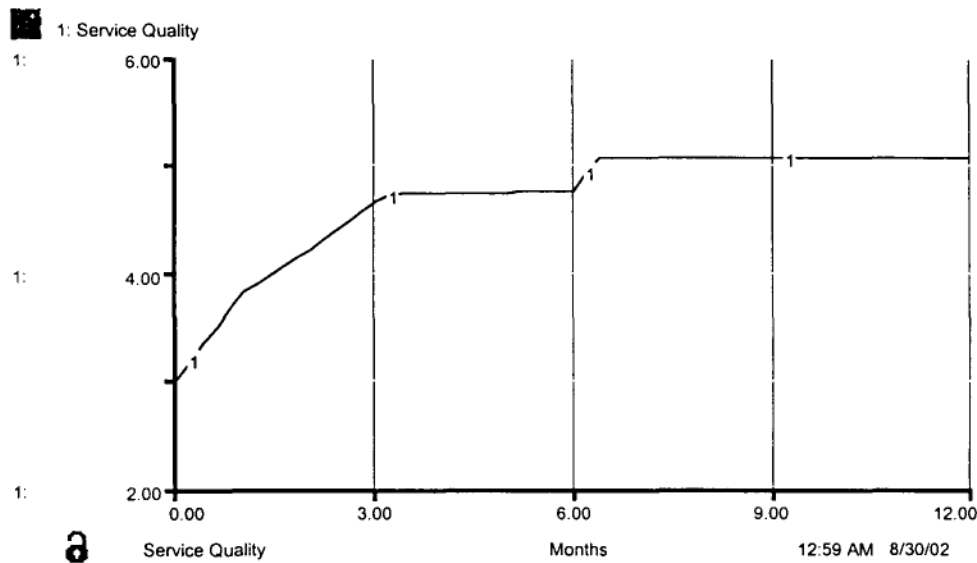


Figure 4-68: Actions in service quality



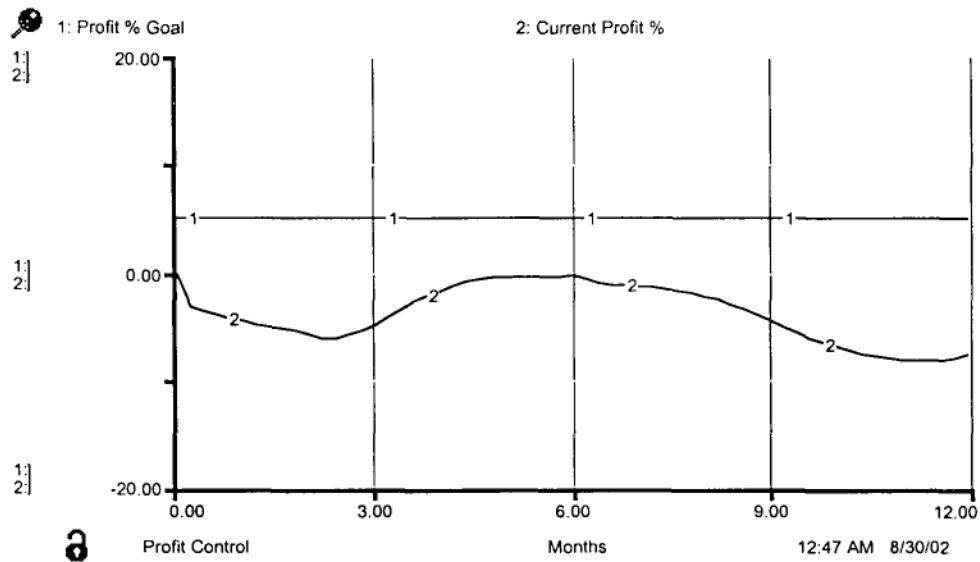


Figure 4-69: Desired and current profit %

With no margin to maneuver, the virtual decision-maker began to manipulate only price to attract customers, as it is shown in Figure 4-70. However, this action punishes the profits.

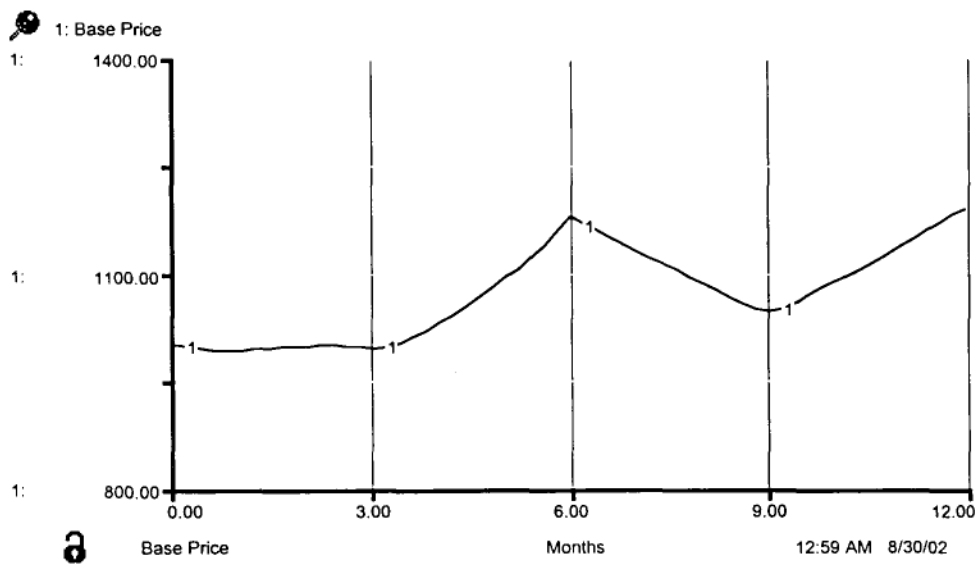


Figure 4-70: Actions in price

The unexpected harmful event creates a scenario that pushes the system to the limit. There is no solution to save the business in this situation. However, the learning from discussion of this scenario will rich the mental models of the participants.

## 4.7 Limitations of the Model

Since a model is a simplified representation of a perceived reality, every model will have its own limitations. In the model under study, they are:

1. The valid time horizon of simulation is twelve months only.
2. The operating point with respect to *Occupancy Percentage* of the hotel is 40% and the operation interval is  $\pm 30\%$ . For one year of time horizon, this restriction of operation was reasonable. The implication of this limitation is given in the next point.
3. The effect of limits of growth is not modeled. Only the segment indicated by letter A in Figure 4-71 is considered. The reason is the definition given by the Reference Modes in Section 4.3.1, and the operational limits declared at point 2 above. This implies the model would represent situations into the interval 10 to 70 % of Occupancy percentage. Thus saturation effects are not required at this stage.

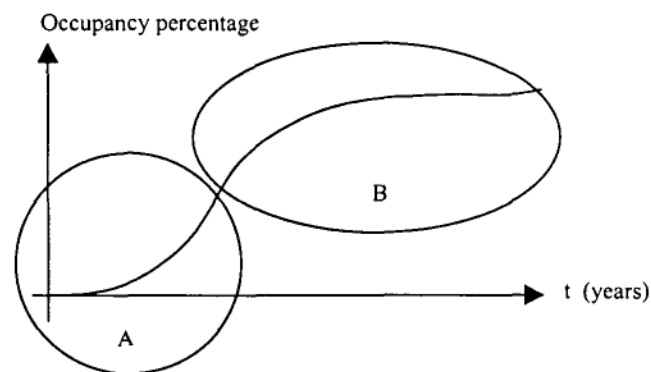


Figure 4-71: Only the behavior of the area "A" is modeled

4. The focus of the model is made on the aggregated relationships that include price, service quality, profits, and occupancy percentage. Effects caused by improvements on other business and operative processes are not taken into account.
5. Competence of the personnel is not included
6. Yield management is not included. The reason was the emphasis on short and long terms benefits, which are the focus of the problem situation. Then the problem was not optimizing revenues at this stage.
7. The Knowledge-Base Fuzzy Systems (FKBS) has been designed for the specific problematic situation model. Even when the problematic situation model represents a

non-linear and coupled systems, it may not work properly for a problematic situation with a dominant non-minimum phase, such as right zeros close the origin and more highly coupled interactions between the outputs.

8. The five-star hotel industry and the specific hotel modeled are not general. They represent a specific hotel industry and hotel for Puerto Vallarta, Mexico in 1996. Also, the model only represents the perspective of the participants in the modeling sessions. The method for acquiring qualitative knowledge is what attempts to be general.

#### 4.7.1 Overbooking Model

One of the limitations of the model was given by the specification that only the first part of the S-Shaped curve should be modeled. However, an extension of the model to capture an overbooking effect can be generated with the following structure of the "Limits to Growth" archetype (Senge, 1990, 95-104,) (Sterman, 2000, 118-127.) The structure is shown in Figure 4-72.

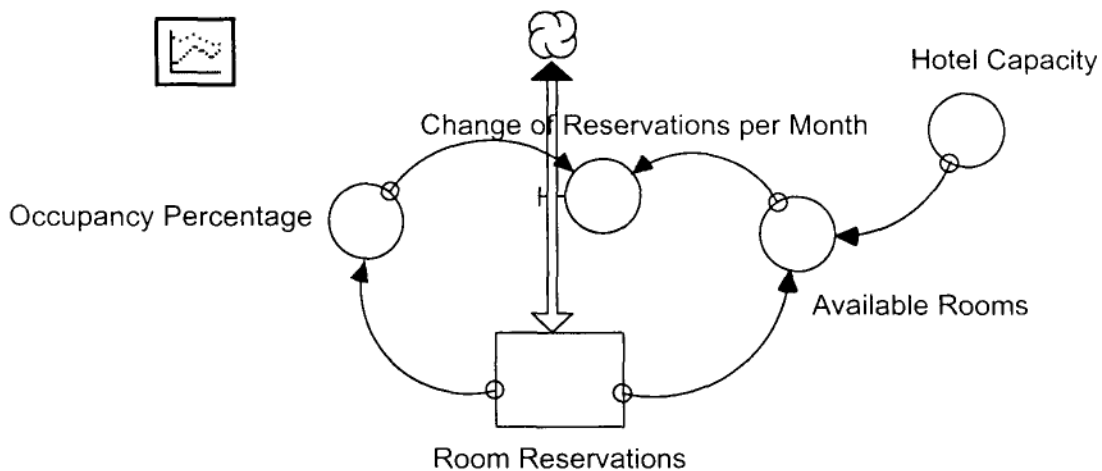


Figure 4-72: Structure of limits to growth

The behavior produced by the structure on *Room Reservations* is shown in Figure 4-73. It is observed how the hotel reaches its capacity close month 15. However, a lack of management on room reservations is presented and the effect of overbooking is observed. The number of reservations made by the hotel surpasses the hotel capacity. Displeased customers by not having their assigned rooms on time spread out this inconvenience. The credibility and confidence of the hotel fall and a decrement of reservations for the next months is a known result.

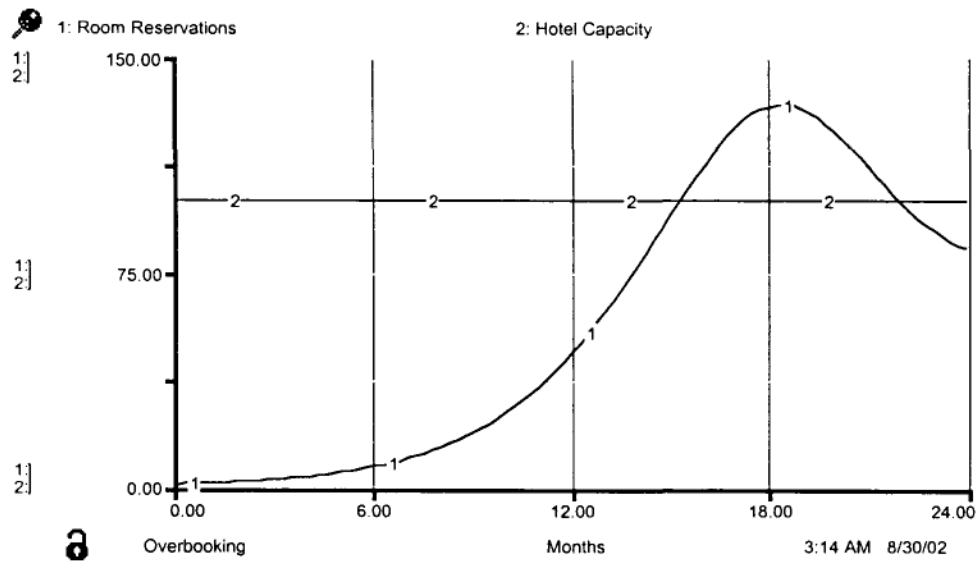


Figure 4-73: Overbooking effect pattern

#### Mathematical equations of the overbooking model.

$$\text{Room\_Reservations}(t) = \text{Room\_Reservations}(t - dt) + (\text{Change\_of\_Reservations\_per\_Month}) * dt$$

$$\text{INIT Room\_Reservations} = 1$$

$$\text{Change\_of\_Reservations\_per\_Month} = \text{Occupancy\_Percentage} * \text{Available\_Rooms} * 0.35$$

$$\text{Available\_Rooms} = \text{Hotel\_Capacity} - \text{Delay}(\text{Room\_Reservations}, 3)$$

$$\text{Hotel\_Capacity} = 100$$

$$\text{Occupancy\_Percentage} = \text{Room\_Reservations} / 100$$



# Chapter 5

## Conclusions

*“All sciences characterize the essential nature of the systems they study. These characterizations are invariable qualitative in nature, for they set the terms with which more detailed knowledge can be developed...”*

(Newell and Simon, ACM Turing Award Lecture, 1976, cited by Luger and Stubblefield, 1993, 29.)

It has been developed and presented a method to realize qualitative knowledge acquisition about dynamics of continuous complex systems using System Dynamics and Fuzzy Logic. The research questions are answered as follows.

### 5.1 Answers to the Research Questions

#### 1. **How to elicit uncertain, incomplete, and qualitative knowledge of the dynamics of complex systems and getting it into a model for computer-based simulation?**

Answer. Following the natural transformation myths-symbols-numbers and representing it via circular reasoning. Myths, constituted by mental models, verbal models, and causal diagrams; Symbols, by diagrams of levels and rates of changes along with a graphical computer language, and Numbers, constituted by algebraic and difference equations. Feedback theory provides the structure of knowledge to be used.

This is done by:

- Using traditional methods for Knowledge Engineer developed by Artificial Intelligence for the planning and considerations of the knowledge acquisition process.
- Using if-then rules (cause-effect relationships) as the atomic element to represent knowledge.
- Using System Thinking approach to establish the slide of the reality to be modeled. This allows: (a) Seeing interrelationships among the elements and process of changes. The knowledge is represented as feedback structures causing perceived behavior in the defined context. The representation becomes pure circular reasoning, and (b) stating focus on the closed boundary of the system and the type of aggregation required.
- Using System Dynamics to acquire and construct a simulation model that represent the set of policies that govern the perceived situation into a computer model.
- Using Fuzzy Logic to represent specifically set of policies used by decision-makers.

It is required in the process:

Two kinds of knowledge: (a) actual knowledge and insight of the system such as properties and how it works, and (b) how these facts can be transferred into a useful model. These two areas of knowledge are called the area of expert domain and the area of the knowledge engineer, respectively.

There are three sources of knowledge and information for system properties:

- a) Experience of experts.
- b) Literature generated and worked out by generation of scientist.
- c) The system itself over which observation and experiments are carried out.

The challenge of this research was the knowledge acquisition of letter (a) Experience of experts.

## 2. When is adequate to use Fuzzy Logic into System Dynamics to represent dynamic complexity?

Answer. Fuzzy Logic is adequately used in representing dynamic complexity into System Dynamic models when:

1. it is used as approximating mapping function instead of a technique to represent vagueness and uncertainty. Fuzzy Logic is not an alternative of probability and statistic Fuzzy Logic is a mathematical discipline to handle interval-based elements, and
2. the details of the decision-maker policies are the central issue and these policies have deeper meaning than those represented in the model. In this manner, it is possible to combine different levels of knowledge in the same model.

## 5.2 On Fuzzy Logic and System Dynamics

On one side, it should be clear that a System Dynamic model is a representation of policies in action. Policies in System Dynamics are like the transfer functions in control engineering. However, the problem in System Dynamics is not control but also finding the structures of policies that are causing the problems in a complex system and then designing policies that improves it. The better results using System Dynamics have been given in Strategic Planning of large companies, sharing visions to create consensus and commitment, to produce learning, and to solve problems or design systems (last goal of System Dynamics). On the other side, the best solutions to problems using Fuzzy Logic have been given in Control Engineering, mainly in direct control, in the operative level. Fuzzy has proved being effective when the mathematical models of what is pretended to be controlled is too expansive to obtained. Low-cost and robust solutions are provided by Fuzzy Logic. This last statement was confirmed in this research.

On complex systems, this kind of systems involves people. One of the challenges by dealing with complex systems is that mathematical language is scarcely used. It is known, on one hand, that complex systems are non-linear, highly coupled and with large time constants (sometimes decades or larger) with regard human time life. On the other hand, another challenge is, for example in business, administration or most social systems, the design an organization or system can not be done in the same manner as the design of a nuclear or thermal power plant. A large number of hours are spent in simulation before constructing a



new design. However, in complex systems the design has to work at first, if not then on the process is fixed.

Two key questions arise during the Conceptualization stage. They are not completely answered by the literature in this context.

Questions:

1. How many *levels* (state variables) does the model have to consider?
2. What variables should it be considered *levels* (state variables)?

Hung V. Vu (Vu, 1997) provides the answer in the context of modeling techniques for physical systems.

Answers:

1. "The number of initial conditions required indicates the number of state variables required to describe the system."
2. "Those variables for which initial conditions are required are chosen as state variables."

### 5.3 On Results of the Research

An alternative method to address the knowledge acquisition "bottleneck" problem in Artificial Intelligent was presented. A Fuzzy Logic-based model represented the knowledge that governs decisions, and a System Dynamics-based model represented the understanding of a business administration process. Both models are interdependence and comprise the acquired knowledge unit.

The results of the research showed that the method is viable.

A relevant result of this research is the finding on the coincidences about the design of the fuzzy structure proposed in Subsection 4.4.2 and the one proposed by (Viljamaa & Koivo, 1993.) After a detailed analysis, it can be concluded that the proposed fuzzy structure is general for a class of process of two inputs - two outputs. It should be tested for processes with dominant behavior of right zeros close origin. These processes present reverse response during the temporary response. Then the fuzzy structure may be cover wider classes of processes. About the similarities of the structures, indeed both are the same. They were designed in different contexts but they arrived at the same structure. Ours in the context of business and administration and

Viljamaa-Koivos's in the context of tuning multivariable fuzzy controllers. The coincidences are: (1) dimensions of the process to be controlled, two inputs - two outputs; (2) number of rules for the fuzzy knowledge base; (3) structure of the linguistic variables, two membership functions; (4) one parameter to define each membership; (5) structure of the rules with four premises and one conclusion, and (6) the method for defuzzification based on singletons. At the same time, the main difference is the number of singletons used. The proposed design uses three singletons. The Viljamaa-Koivos's one uses nine.

## **5.4 On the Strength and Weakness of the Method**

The strength of the method to acquire qualitative knowledge is the combination of Fuzzy Logic and System Dynamics to construct a model that contains two levels of abstraction. The rules that are used by a decision-maker or group of decision-makers to control a business process (using Fuzzy Logic) and the understanding of the business process under study (using System Dynamics). This model then may be used to communicate and share a vision into an organization, or inside an intelligent system, for instance, one based on Model Base Reasoning technique.

The weakness of the method is the dependence of skills of the knowledge engineer to facilitate the elicitation process mostly face-to-face with the group of participants, and the background and skills to represent qualitative knowledge using Fuzzy Logic and System Dynamics.

## **5.5 On the Concept of Knowledge**

An important conclusion is on the concept of knowledge. Knowledge is the capacity for effective response. Peter Senge defined knowledge as "the capacity for effective action" in (McKelvey, et al., 2001, 78.) In our definition, it is emphasized the reactive nature of knowledge. In Senge's definition, it is emphasized the result or final product that is a decision, which is an action in his context. Close related concepts are the followings. Comprehension is the association of knowledge that gives a capacity of effective response to new patterns. Learning as the process to construct significance (Martínez de Ramos, 2001, 11). "Intelligence refers to our effective use of knowledge" (Pór and Molloy, 2000, 2.)

Why is knowledge more important in economy nowadays than in the past?

1. Because design task has being getting higher relevance than solving problem task.
2. Because the concept of knowledge has nowadays a wider connotation in global economy. It covers all the intangible assets that provide capacity of effective response to enterprises, industries, nations, etc. The intangible assets are, for example, customer loyalty and confidence, brand of a product, and perceived value of the customer from the products.

The challenges having these capacities of effective response are how to identify, register in countable books, and capitalize them. In order to tackle this problem, which consists in finding know-how's, the analysis method is being applied in human organizations. The method is based in finding the indivisible unit by putting apart, understanding the parts and integrating the understandings in order to understand the whole. In this process, the indivisible part results to be the individual person in organizations. Now the technical issue is how to put the knowledge of the person into a machine. (Annie Brooking, 1999) has made an interesting question. Are people the more important capital in our company or their knowledge? The research in this document was focused in generating a know-how about putting qualitative knowledge possesses by humans on dynamics of complex system in a machine. Other issues are how to create knowledge and how to facilitate learning. Certainly, these themes are worthy to work in other researches.

## 5.6 Further Research

1. The simulation model can be part of a Knowledge Based Simulation (KBS) to expand the capacity of Knowledge-Based Systems and try to answer questions of the type: Can the situation A happen? What conditions must be present to observe event B? Questions proposed by (Rothenberg, 1990.) These systems overpass their predecessors by answering questions beyond "What if."
2. In the same manner, Model Base Reasoning (MBR) techniques (Scarl, 1990) can expand their range of applications and not only to tackle problems based on scientific knowledge, but also applications in business and social areas where systems are considered soft. Designing this kind of systems has still a great component of intuition and good will. As it is known, the big challenge in our days is how to balance the development of our social systems with the development of our technological systems.

3. Automate the knowledge engineer intervention.
4. Construct a higher layer of software that administrates the simulation model to gather information and explain behaviors.
5. Generate a study of decision-maker based on the constructed simulator to perceive the general pattern of decision-makers during their task.
6. Develop a FKBS based on Takagi-Sugeno fuzzy model to compare advantages in knowledge acquisition process.
7. The hotel model should consider the yield management strategy for next stage. To implement yield management, the simulator should include indicators of how many rooms are reserved and available at a specific time. Also the simulator should allow independently assigning prices per customer type. That would imply to have a set of at least 8 prices. One for low-priced rooms and another for high-priced per customer profile.
8. Extension of the model to include saturation or limits to growth. In this point, it is suggested to consider three types of limits: (1) limits based on the believes and values of the managers, (2) limits based on physical and organizational restrictions of the hotel, and (3) limits based on market share of the specific zone.
9. It is suggested to carry out the next step of model validation that consists on using real data to adjust parameters and check the fitness of the structure. Then the model, as a tested hypothesis, may be wished to predict or forecast future behaviors and events of the business.
10. It is recommended to extent the research toward the learning effects given in the participants during the modeling process. Participants were constantly involved in reflections. The observed effect was a better understanding of what they already knew. In this thesis, the attention was paid only on the technical issues of the qualitative knowledge acquisition addressed to the machine.



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# Appendix 1

## Equations of the Model

$AccumAgencies(t) = AccumAgencies(t - dt) + (Change\_P\_Agencies) * dt$   
 INIT AccumAgencies = .2

$Change\_P\_Agencies = ActivatedReserv\_Agencies - 1$   
 $AccumAirlines(t) = AccumAirlines(t - dt) + (Change\_P\_Airlines) * dt$   
 INIT AccumAirlines = .35

$Change\_P\_Airlines = ActivatedReserv\_Airlines - 1$   
 $AccumCommercials(t) = AccumCommercials(t - dt) + (Change\_P\_Commercials) * dt$   
 INIT AccumCommercials = .15

$Change\_P\_Commercials = ActivatedReserv\_Commercials - 1$   
 $AccumDirects(t) = AccumDirects(t - dt) + (Change\_P\_Directs) * dt$   
 INIT AccumDirects = .3

$Change\_P\_Directs = ActivatedReserv\_Directs - 1$   
 $ActivatedReserv\_Agencies(t) = ActivatedReserv\_Agencies(t - dt) + (Confirm\_2 - ReservOut\_Agencies) * dt$   
 INIT ActivatedReserv\\_Agencies = 1  
 TRANSIT TIME = 1  
 INFLOW LIMIT = INF  
 CAPACITY = INF

$Confirm\_2 = CONVEYOR\ OUTFLOW$   
 $ReservOut\_Agencies = CONVEYOR\ OUTFLOW$   
 $ActivatedReserv\_Airlines(t) = ActivatedReserv\_Airlines(t - dt) + (Confirm\_3 - ReservOut\_Airlines) * dt$



INIT ActivatedReserv\_Airlines = 1

TRANSIT TIME = 1

INFLOW LIMIT = INF

CAPACITY = INF

Confirm\_3 = CONVEYOR OUTFLOW

ReservOut\_Airlines = CONVEYOR OUTFLOW

ActivatedReserv\_Commercials(t) = ActivatedReserv\_Commercials(t - dt) + (Confirm\_4 -

Salida\_Reserv\_Comerciales) \* dt

INIT ActivatedReserv\_Commercials = 1

TRANSIT TIME = 1

INFLOW LIMIT = INF

CAPACITY = INF

Confirm\_4 = CONVEYOR OUTFLOW

Salida\_Reserv\_Comerciales = CONVEYOR OUTFLOW

ActivatedReserv\_Directs(t) = ActivatedReserv\_Directs(t - dt) + (Confirm\_1 - ReservOut\_Directs) \* dt

INIT ActivatedReserv\_Directs = 1

TRANSIT TIME = 1

INFLOW LIMIT = INF

CAPACITY = INF

Confirm\_1 = CONVEYOR OUTFLOW

ReservOut\_Directs = CONVEYOR OUTFLOW

RequestedReserv\_Agencies(t) = RequestedReserv\_Agencies(t - dt) + (Reserv\_Agencies - Confirm\_2) \* dt

INIT RequestedReserv\_Agencies = 2

TRANSIT TIME = 2

INFLOW LIMIT = INF

CAPACITY = INF

Reserv\_Agencies = 1+PNRAgencies

Confirm\_2 = CONVEYOR OUTFLOW

RequestedReserv\_Airlines(t) = RequestedReserv\_Airlines(t - dt) + (Reserv\_Airlines - Confirm\_3) \* dt

INIT RequestedReserv\_Airlines = 2

TRANSIT TIME = 2

INFLOW LIMIT = INF

CAPACITY = INF

Reserv\_Airlines = 1+PNRAirlines

Confirm\_3 = CONVEYOR OUTFLOW

RequestedReserv\_Commercials(t) = RequestedReserv\_Commercials(t - dt) + (Reserv\_Commercials - Confirm\_4) \* dt

INIT RequestedReserv\_Commercials = 2

TRANSIT TIME = 2

INFLOW LIMIT = INF

CAPACITY = INF

Reserv\_Commercials = 1+PNRCommercials

Confirm\_4 = CONVEYOR OUTFLOW

RequestedReserv\_Directs(t) = RequestedReserv\_Directs(t - dt) + (Reserv\_Directos - Confirm\_1) \* dt

INIT RequestedReserv\_Directs = 2

TRANSIT TIME = 2

INFLOW LIMIT = INF

CAPACITY = INF

Reserv\_Directos = 1+PNRDirects

Confirm\_1 = CONVEYOR OUTFLOW

PSneg(t) = PSneg(t - dt) + (PSneg\_dot) \* dt

INIT PSneg = -100

PSneg\_dot = IF(ABS(Profit\_Gap)>Bias\_Price)THEN(GammaPSN\*PMuN\*Profit\_Gap)ELSE(0)

PSpos(t) = PSpos(t - dt) + (PSpos\_dot) \* dt

INIT PSpos = 100

PSpos\_dot = IF(abs(Profit\_Gap)>Bias\_Price)THEN(GammaPSP\*PMuP\*Profit\_Gap)ELSE(0)

QSneg(t) = QSneg(t - dt) + (QSneg\_dot) \* dt

INIT QSneg = -.8

QSneg\_dot = IF(abs(Occ\_Perc\_Gap)>Bias\_Occ)THEN(GammaQSN\*QMuN\*Occ\_Perc\_Gap)ELSE(0)

QSpos(t) = QSpos(t - dt) + (QSpos\_dot) \* dt

INIT QSpos = .8

QSpos\_dot = IF(abs(Occ\_Perc\_Gap)>Bias\_Occ)THEN(GammaQSP\*QMuP\*Occ\_Perc\_Gap)ELSE(0)

Bias\_Occ = 2

Bias\_Price = 2

```

GammaPSN = IF(Adaptation_Capability=1)THEN(Gamma_P)ELSE(0)
GammaPSP = IF(Adaptation_Capability=1)THEN(Gamma_P)ELSE(0)
GammaQSN = IF(Adaptation_Capability=1)THEN(Gamma_Q)ELSE(0)
GammaQSP = IF(Adaptation_Capability=1)THEN(Gamma_Q)ELSE(0)
Gamma_P = 1
Gamma_Q = 2/100
PMuN = MEAN(pw2,pw3,pw4,pw8,pw12)
PMuP = MEAN(pw5,pw9,pw13,pw14,pw15)
QMuN = MEAN(qw16)
QMuP = MEAN(qw1,qw2,qw3,qw4)
Change_in_Agencies = 0.5*Change_in_Agencies_by_Quality+0.5*Change_in_Agencies_by_Price
Change_in_Airlines = 0.5*Change_in_Airlines_by_Quality+0.5*Change_in_Airlines_by_Price
Change_in_Commercials = 0.5*Change_in_Commercials_by_Quality+0.5*Change_in_Commer_by_Price
Change_in_Directs = 0.5*Change_in_Directs_by_Quality+0.5*Change_in_Directs_by_Price
CompetenceRoom = Five_Star_Market-HotelRooms
HotelRooms = Five_Star_Market*PDimHotel
NominalHotelRooms = Five_Star_Market*PHotel
PAerolineas = AccumAirlines/SumPMixture
PAgencias = AccumAgencies/SumPMixture
PComerciales = AccumCommercials/SumPMixture
PDimHotel = PHotel+P_Activ_Reserv-1
PDirectos = AccumDirects/SumPMixture
Rooms2Agencies = HotelRooms*PAgencias
Rooms2Airlines = HotelRooms*PAerolineas
Rooms2Comerciales = HotelRooms*PComerciales
Rooms2Directs = HotelRooms*PDirectos
SumPMixture = AccumDirects+AccumAgencies+AccumAirlines+AccumCommercials
Five_Star_Market = GRAPH(TIME)
(1.00, 38684), (2.00, 42005), (3.00, 38526), (4.00, 33854), (5.00, 22387), (6.00, 22387), (7.00, 31475),
(8.00, 31360), (9.00, 19753), (10.0, 25021), (11.0, 29620), (12.0, 30782), (13.0, 30782)
PHotel = GRAPH(TIME)
(1.00, 0.134), (2.00, 0.119), (3.00, 0.121), (4.00, 0.121), (5.00, 0.138), (6.00, 0.13), (7.00, 0.13), (8.00,
0.122), (9.00, 0.131), (10.0, 0.113), (11.0, 0.132), (12.0, 0.178), (13.0, 0.178)
Accumulated_Costs(t) = Accumulated_Costs(t - dt) + (Total_Costs) * dt
INIT Accumulated_Costs = 0.01

Total_Costs = Costs4Directs+Costs4Airlines+Costs4Agencies+Costs4Commercials+Service_Quality_Cost

```

Costs4Agencies = Rooms2Agencies\*VarCosts4Agencies  
 Costs4Airlines = Rooms2Airlines\*VarCosts4Aerolneas  
 Costs4Commercials = Rooms2Commercials\*VarCosts4Commercials  
 Costs4Directs = Rooms2Directs\*VarCosts4Directs  
 VarCosts4Aerolneas = 250  
 VarCosts4Agencies = 250  
 VarCosts4Commercials = 200  
 VarCosts4Directs = 300  
 Service\_Quality\_Cost = GRAPH(Service\_Quality)  
 (1.00, 1.7e+006), (2.00, 2e+006), (3.00, 2.4e+006), (4.00, 2.5e+006), (5.00, 2.7e+006)  
 PFKBS(t) = PFKBS(t - dt) + (Change\_in\_price) \* dt  
 INIT PFKBS = Price

Change\_in\_price = (PN\*Ps1+PZ\*Ps2+PP\*Ps3)/(PN+PZ+PP)  
 QFKBS(t) = QFKBS(t - dt) + (Change\_of\_Q) \* dt  
 INIT QFKBS = Quality

Change\_of\_Q =  
 IF((QFKBS<4.98)OR(((QN\*Qs1+QZ\*Qs2+QP\*Qs3)/(QN+QZ+QP)<0))THEN(((QN\*Qs1+QZ\*Qs2+QP\*Qs3)/(QN+QZ+QP))ELSE(0)  
 Ps1 = PSneg  
 Ps2 = 0  
 Ps3 = PSpos  
 Qs1 = QSneg  
 Qs2 = 0  
 Qs3 = QSpos  
 PN = MAX(pw2,pw3,pw4,pw8,pw12)  
 PP = MAX(pw5,pw9,pw13,pw14,pw15)  
 PZ = MAX(pw1,pw6,pw7,pw10,pw11,pw16)  
 QN = MAX(qw16)  
 QP = MAX(qw1,qw2,qw3,qw4)  
 QZ = MAX(qw5,qw6,qw7,qw8,qw9,qw10,qw11,qw12,qw13,qw14,qw15)  
 pw1 = MIN(x1NV,x1NVdot,x2NV,x2NVdot)  
 pw10 = MIN(x1PV,x1NVdot,x2NV,x2PVdot)  
 pw11 = MIN(x1PV,x1NVdot,x2PV,x2NVdot)  
 pw12 = MIN(x1PV,x1NVdot,x2PV,x2PVdot)  
 pw13 = MIN(x1PV,x1PVdot,x2NV,x2NVdot)

$$pw14 = \text{MIN}(x1PV, x1PVdot, x2NV, x2PVdot)$$

$$pw15 = \text{MIN}(x1PV, x1PVdot, x2PV, x2NVdot)$$

$$pw16 = \text{MIN}(x1PV, x1PVdot, x2PV, x2PVdot)$$

$$pw2 = \text{MIN}(x1NV, x1NVdot, x2NV, x2PVdot)$$

$$pw3 = \text{MIN}(x1NV, x1NVdot, x2PV, x2NVdot)$$

$$pw4 = \text{MIN}(x1NV, x1NVdot, x2PV, x2PVdot)$$

$$pw5 = \text{MIN}(x1NV, x1PVdot, x2NV, x2NVdot)$$

$$pw6 = \text{MIN}(x1NV, x1PVdot, x2NV, x2PVdot)$$

$$pw7 = \text{MIN}(x1NV, x1PVdot, x2PV, x2NVdot)$$

$$pw8 = \text{MIN}(x1NV, x1PVdot, x2PV, x2PVdot)$$

$$pw9 = \text{MIN}(x1PV, x1NVdot, x2NV, x2NVdot)$$

$$qw1 = \text{MIN}(x1NV, x1NVdot, x2NV, x2NVdot)$$

$$qw10 = \text{MIN}(x1PV, x1NVdot, x2NV, x2PVdot)$$

$$qw11 = \text{MIN}(x1PV, x1NVdot, x2PV, x2NVdot)$$

$$qw12 = \text{MIN}(x1PV, x1NVdot, x2PV, x2PVdot)$$

$$qw13 = \text{MIN}(x1PV, x1PVdot, x2NV, x2NVdot)$$

$$qw14 = \text{MIN}(x1PV, x1PVdot, x2NV, x2PVdot)$$

$$qw15 = \text{MIN}(x1PV, x1PVdot, x2PV, x2NVdot)$$

$$qw16 = \text{MIN}(x1PV, x1PVdot, x2PV, x2PVdot)$$

$$qw2 = \text{MIN}(x1NV, x1NVdot, x2NV, x2PVdot)$$

$$qw3 = \text{MIN}(x1NV, x1NVdot, x2PV, x2NVdot)$$

$$qw4 = \text{MIN}(x1NV, x1NVdot, x2PV, x2PVdot)$$

$$qw5 = \text{MIN}(x1NV, x1PVdot, x2NV, x2NVdot)$$

$$qw6 = \text{MIN}(x1NV, x1PVdot, x2NV, x2PVdot)$$

$$qw7 = \text{MIN}(x1NV, x1PVdot, x2PV, x2NVdot)$$

$$qw8 = \text{MIN}(x1NV, x1PVdot, x2PV, x2PVdot)$$

$$qw9 = \text{MIN}(x1PV, x1NVdot, x2NV, x2NVdot)$$

$$a1 = 10$$

$$a1dot = 5$$

$$a2 = 5$$

$$a2dot = 10$$

$$\text{Current\_Occ\_}\% = (\text{OccupancyPercentage} - \text{Last\_Year\_Occupancy\_Percentage}) / \text{Last\_Year\_Occupancy\_Percentage} * 100$$

$$\text{Current\_Profit\_}\% = (\text{Accumulated\_Incomes} - \text{Accumulated\_Costs}) / \text{Accumulated\_Costs} * 100$$

$$e1 = \text{Occ\_Perc\_Gap}$$

$$e1dot = \text{Occ\_Perc\_Gap} - \text{delay}(\text{Occ\_Perc\_Gap}, 1, 0)$$

$$e2 = \text{Profit\_Gap}$$

```

e2dot = Profit_Gap-delay(Profit_Gap,1,0)
Occupancy_%_Goal = 10
Occ_Perc_Gap = Current_Occ_%-Occupancy_%_Goal
Profit_%_Goal = 5
Profit_Gap = Current_Profit_%-Profit_%_Goal
x1N = IF(e1<=-a1)THEN(1)ELSE((a1-e1)/(2*a1))
x1Ndot = IF(e1dot<=-a1dot)THEN(1)ELSE((a1dot-e1dot)/(2*a1dot))
x1NV = IF(x1N<0)THEN(0)ELSE(x1N)
x1NVdot = IF(x1Ndot<0)THEN(0)ELSE(x1Ndot)
x1P = IF(e1>=a1)THEN(1)ELSE((a1+e1)/(2*a1))
x1Pdot = IF(e1dot>=a1dot)THEN(1)ELSE((a1dot+e1dot)/(2*a1dot))
x1PV = IF(x1P<0)THEN(0)ELSE(x1P)
x1PVdot = IF(x1Pdot<0)THEN(0)ELSE(x1Pdot)
x2N = IF(e2<=-a2)THEN(1)ELSE((a2-e2)/(2*a2))
x2Ndot = IF(e2dot<=-a2dot)THEN(1)ELSE((a2dot-e2dot)/(2*a2dot))
x2NV = IF(x2N<0)THEN(0)ELSE(x2N)
x2NVdot = IF(x2Ndot<0)THEN(0)ELSE(x2Ndot)
x2P = IF(e2>=a2)THEN(1)ELSE((a2+e2)/(2*a2))
x2Pdot = IF(e2dot>=a2dot)THEN(1)ELSE((a2dot+e2dot)/(2*a2dot))
x2PV = IF(x2P<0)THEN(0)ELSE(x2P)
x2PVdot = IF(x2Pdot<0)THEN(0)ELSE(x2Pdot)
Accumulated_Incomes(t) = Accumulated_Incomes(t - dt) + (Total_Incomes) * dt
INIT Accumulated_Incomes = 0.01

Total_Incomes = Incomes_FromDirects+PaidBills+IncomesFromAirlines+IncomesFromCommercials
Bills2BPaid(t) = Bills2BPaid(t - dt) + (IncomesFromAgencies - Payments) * dt
INIT Bills2BPaid = 0
    TRANSIT TIME = 2
    INFLOW LIMIT = INF
    CAPACITY = INF

IncomesFromAgencies = Rooms2Agencies*Fare4Agencies
Payments = CONVEYOR OUTFLOW
PaidBills(t) = PaidBills(t - dt) + (Payments - File) * dt
INIT PaidBills = 0
    TRANSIT TIME = 1
    INFLOW LIMIT = INF

```

CAPACITY = INF

Payments = CONVEYOR OUTFLOW

File = CONVEYOR OUTFLOW

Fare4Agencies = .85\*Base\_Price

Fare4Airlines = .75\*Base\_Price

Fare4Commercials = .9\*Base\_Price

Fare4Directos = 1\*Base\_Price

IncomesFromAirlines = Rooms2Airlines\*Fare4Airlines

IncomesFromCommercials = Rooms2Commercials\*Fare4Commercials

Incomes\_FromDirects = Rooms2Directs\*Fare4Directos

Occupancy\_ISE(t) = Occupancy\_ISE(t - dt) + (OccSquareDeviation) \* dt

INIT Occupancy\_ISE = 0

OccSquareDeviation = Occ\_Perc\_Gap\*Occ\_Perc\_Gap

Profit\_ISE(t) = Profit\_ISE(t - dt) + (ProfitSquareDeviation) \* dt

INIT Profit\_ISE = 0

ProfitSquareDeviation = Profit\_Gap\*Profit\_Gap

Current\_Month = TIME

Occ\_Perform\_Fnc = SQRT(Occupancy\_ISE)/Current\_Month

Profit\_Perform\_Fnc = SQRT(Profit\_ISE)/Current\_Month

Base\_Price = IF(Fuzzy\_Decision\_Making=1)THEN(PFKBS)ELSE(Price)

Change\_in\_Agencies\_by\_Price = Change\_in\_Agencies\_2

Change\_in\_Airlines\_by\_Price = Change\_in\_Airlines\_2

Change\_in\_Commer\_by\_Price = Change\_in\_Commercials\_2

Change\_in\_Directs\_by\_Price = Change\_in\_Directs\_2

RefFare = 800

RefFare4Agencies = 0.85\*RefFare

RefFare4Airlines = 0.750\*RefFare

RefFare4Commercials = 0.90\*RefFare

RefFare4Directos = RefFare\*1

Satisfaction\_of\_Agencies\_2 = IF(RefFare4Agencies<0.85\*Base\_Price)THEN((-4\*1.05/RefFare4Agencies)\*0.85\*Base\_Price+9)ELSE(5)

Satisfaction\_of\_Airlines\_2 = IF(RefFare4Airlines<0.8\*Base\_Price)THEN((-4\*1.05/RefFare4Airlines)\*0.8\*Base\_Price+9)ELSE(5)

```

Satisfaction_of_Commercials_2 = IF(RefFare4Commercials<0.9*Base_Price)THEN((-
4*1.05/RefFare4Commercials)*0.9*Base_Price+9)ELSE(5)
Satisfaction_of_Directs_2 = IF(RefFare4Directos<1*Base_Price)THEN((-
4*1.05/RefFare4Directos)*1*Base_Price+9)ELSE(5)
Change_in_Agencies_2 = GRAPH(Satisfaction_of_Agencies_2)
(1.00, -0.3), (2.00, -0.1), (3.00, -0.05), (4.00, 0.00), (5.00, 0.15)
Change_in_Airlines_2 = GRAPH(Satisfaction_of_Airlines_2)
(1.00, -0.35), (2.00, -0.1), (3.00, -0.05), (4.00, 0.00), (5.00, 0.15)
Change_in_Commercials_2 = GRAPH(Satisfaction_of_Commercials_2)
(1.00, -0.3), (2.00, -0.1), (3.00, -0.05), (4.00, 0.00), (5.00, 0.15)
Change_in_Directs_2 = GRAPH(Satisfaction_of_Directs_2)
(1.00, -0.3), (2.00, -0.1), (3.00, -0.05), (4.00, 0.00), (5.00, 0.15)
Profile_of_Agencies = 4
Profile_of_Airlines = 3
Profile_of_Commercials = 4
Profile_of_Directs = 5
Satisfaction_of_Agencies = IF(Profile_of_Agencies>Service_Quality)THEN(5-(Profile_of_Agencies-
Service_Quality))ELSE(5)
Satisfaction_of_Airlines = IF(Profile_of_Airlines>Service_Quality)THEN(5-(Profile_of_Airlines-
Service_Quality))ELSE(5)
Satisfaction_of_Commercials = IF(Profile_of_Commercials>Service_Quality)THEN(5-
(Profile_of_Commercials-Service_Quality))ELSE(5)
Satisfaction_of_Directs = IF(Profile_of_Directs>Service_Quality)THEN(5-(Profile_of_Directs-
Service_Quality))ELSE(5)
Service_Quality = IF(Fuzzy_Decision_Making=1)THEN(QFKBS)ELSE(Quality)
Change_in_Agencies_by_Quality = GRAPH(Satisfaction_of_Agencies)
(1.00, -0.28), (2.00, -0.15), (3.00, -0.05), (4.00, 0.00), (5.00, 0.1)
Change_in_Airlines_by_Quality = GRAPH(Satisfaction_of_Airlines)
(1.00, -0.25), (2.00, -0.15), (3.00, -0.05), (4.00, 0.005), (5.00, 0.06)
Change_in_Commercials_by_Quality = GRAPH(Satisfaction_of_Commercials)
(1.00, -0.28), (2.00, -0.15), (3.00, -0.05), (4.00, 0.00), (5.00, 0.1)
Change_in_Directs_by_Quality = GRAPH(Satisfaction_of_Directs)
(1.00, -0.3), (2.00, -0.15), (3.00, -0.05), (4.00, -0.03), (5.00, 0.1)
P_Activ_Reserv(t) = P_Activ_Reserv(t - dt) + (Confirm_5 - Reserv_Out) * dt
INIT P_Activ_Reserv = 1
TRANSIT TIME = 1
INFLOW LIMIT = INF

```



CAPACITY = INF

Confirm\_5 = CONVEYOR OUTFLOW

Reserv\_Out = CONVEYOR OUTFLOW

Reg\_of\_Reserv(t) = Reg\_of\_Reserv(t - dt) + (DeltaReserv - Confirm\_5) \* dt

INIT Reg\_of\_Reserv = 2

TRANSIT TIME = 2

INFLOW LIMIT = INF

CAPACITY = INF

DeltaReserv = 1+(SumNRHotel)/HotelRooms

Confirm\_5 = CONVEYOR OUTFLOW

Hotel\_Capacity = 9125

Last\_Year\_Occupancy\_Percentage = NominalHotelRooms/Hotel\_Capacity\*100

NRAgencies = Rooms2Agencies\*Change\_in\_Agencies

NRAirlines = Rooms2Airlines\*Change\_in\_Airlines

NRCommercials = Rooms2Commercials\*Change\_in\_Commercials

NRDirects = Rooms2Directs\*Change\_in\_Directs

OccupancyPercentage = IF(HotelRooms>0)THEN(HotelRooms/Hotel\_Capacity\*100)ELSE(0)

PNRAgencies = NRAgencies/HotelRooms

PNRAirlines = NRAirlines/HotelRooms

PNRCommercials = NRCommercials/HotelRooms

PNRDirects = NRDirects/HotelRooms

SumNRHotel = NRDirects+NRAgencies+NRCommercials+NRAirlines

Adaptation\_Capability = 1

Fuzzy\_Decision\_Making = 1

Price = 1000

Quality = 3

Zero\_reference = 0



