uOttawa

L'Université canadienne
Canada's university

FACULTÉ DES ÉTUDES SUPÉRIEURES ET POSTOCTORALES

uOttawa

L'Université canadienne
Canada's university

FACULTY OF GRADUATE AND POSDOCTORAL STUDIES

Amir Mir

AUTEUR DE LA THÈSE / AUTHOR OF THESIS

M.Sc. (Systems Science)

GRADE / DEGREE

Systems Science

FACULTÉ, ÉCOLE, DÉPARTEMENT / FACULTY, SCHOOL, DEPARTMENT

Surveillance of Partially Observable Systems

TITRE DE LA THÈSE / TITLE OF THESIS

Dr. Daniel E. Lane

DIRECTEUR (DIRECTRICE) DE LA THÈSE / THESIS SUPERVISOR

CO-DIRECTEUR (CO-DIRECTRICE) DE LA THÈSE / THESIS CO-SUPERVISOR

EXAMINATEURS (EXAMINATRICES) DE LA THÈSE / THESIS EXAMINERS

Dr. Kevin Brand

Dr. Wojtek Michalowski

Gary W. Slater

Le Doyen de la Faculté des études supérieures et postdoctorales / Dean of the Faculty of Graduate and Postdoctoral Studies

Note:

University of Ottawa
Master's Program in System Science

Thesis

Surveillance of Partially Observable Systems

Student Name: Amir Mir
Student Number: 1304261

Thesis Director:
Professor Daniel E. Lane

Faculty of Graduate and Post Doctorate Study
Department of System Science
University of Ottawa

April 07th, 2008

Your file Votre référence
ISBN: 978-0-494-48487-6
Our file Notre référence
ISBN: 978-0-494-48487-6

Acknowledgment

I would like to offer my sincere thanks to Professor Daniel E. Lane, my advisor, for his generosity of helping me to complete this research. I am deeply indebted to him for his constant support. Without his help, this work would never have been completed.

I would like to thank the members of my defense committee, Professor Ted Yeap, Professor Wojtek Michalowski and Professor Kevin Brand, for their advice and patience. Also, my special thanks go to Ms. Monique Walker, the secretary and advisor of our department, for her great help and support throughout all these years of study.

Finally, I would like to thank my family for their support. I am deeply grateful to my mother, for her unconditional help.

I dedicate this thesis to my mother and father.

Amir Mir

Table of Contents

List of Figures

List of Tables

Abstract

Surveillance of a partially observable system is complex. There are many systems that can be considered as partially observable due to their unknown or partially known structures or the nature of their unknown products and/or partially known results.

The impacts of the consumption of genetically modified food (GM) are an example of a system that is only partially observable. The safety of genetically modified foods (GM) products has caused much controversy. Absence of sufficient and reliable information prevents neither certain confidence about the harmlessness of product consumption, nor any certain conclusion to merit a ban for fear of harm. The lack of any reliable or conclusive post-market observation and consumption effects information, make it difficult to establish a global protocol for such products.

This paper introduces a model for the analysis of partially observable information from the surveillance of post-market consumption of systems such as genetically modified foods (GM) products. This model uses Markov Chains, paired with a Bayesian updating function to estimate the statistical impacts of surveillance observations and modified surveillance policies.

A case study on population health status is used as an illustrative example, which is modeled to demonstrate the impact of policy interventions on simulated data. A cost decision analysis model is also applied to illustrate the impact of policy intervention costs. The model uses a first order Markov chain to estimate the period-over-period change in health status and a Bayesian updating procedure to estimate the population health status based on observations from post-market surveillance. The results show how observation samples can be used to provide information on system changes and improvements.

1. Introduction

As technology expands, reliability, performance and safety become more and more important. The safety of a population has been always a priority, when it comes to introduction of new products or technology. Monitoring of system behavior helps to track hazards to people. Surveillance is a method used as a tool to help understand or control the impacts of new products or technology.

Surveillance is the monitoring of responses and adverse effects. Systems surveillance is the process of monitoring the performance of objects, a population, or processes within a system to understand or to achieve a desired standard of performance. The simplest components of surveillance are observation, examination, analysis and supervision. Surveillance is a systematic observation method for monitoring a system, for instance, monitoring the diseases in a population, in order to be able to detect changes in its patterns and then to be able to control them. (Collegeboard, 2008) Monitoring population health is an important issue, yet it is a difficult task. Health surveillance has an important rule for observation and controlling of health status.

The consumption of new products and foods have an effect on and influence population health. Introducing a new product requires approval of its safety. Pre and Post-market surveillance play a substantial and considerable role in providing safety monitoring and control of new products. Post-market surveillance is essential to monitor, detect, and maintain balance between the benefit and risks, as well as addressing safety, and quality of health products after they enter the marketplace (Health Canada-B, 2007).

New technology has brought new solutions to respond to demands for new food resources. As the population grows, land becomes increasingly expensive and less accessible. Unlike 50 years ago, traditional means of agriculture are no longer able to provide enough supplies to meet demand. Recently, genetic engineering has introduced new techniques to improve food's growth characteristics, shelf life, and nutritional balance.

Since the introduction of genetically modified (GM) food into the market, even after it has been declared safe under pre-market testing, the case of suspicion and controversy has never been completely removed in the post-market period. Thus genetically modified (GM) food represents an applied area of demonstration for the importance of surveillance of partially observable health systems.

Since all GM products are complex, their influences on health are controversial and their effects on the safety of the food chain are only partially known and observable. In any case, their effect on health cannot be easily understood; therefore the direct and indirect effects of GM production-consumption on the health system are only partially observable. One response to this problem is to develop an ongoing monitoring and surveillance system. The objective of a surveillance model is to provide a better understanding of the system that is only partially observable. Surveillance involves a series of actions including the collection, simulation, integration, analysis, control, and intervention of incoming data and information of the performance of the system in question.

1.1 History

In 2002, Federal government of Canada gave the responsibility for the post-market surveillance of the products, devices, drugs, and foods to the Marketed Health Products Directorate (MHPD) as part of Health Products and Food Branch (HPFB) (Health Canada-B, 2007). In 2007, Health Canada estimated that there are 22,000 pharmaceutical products, 42,000 natural health products and 50,000 medical devices on the Canadian market. Post-market surveillance plays an important role in monitoring of these products and devices. (Health Canada-B, 2007)

Genetically modified (GM) foods are examples of products requiring pre and post market surveillance on their partially observable impact on population health. There is not much information about the impact of GM products on human health that may be considered detailed and accurate.

The world's first genetically modified food was produced in 1991 by Calgene, a Californian company. The first GM product was a tomato. They called it Flavr Savr. The news about the first genetically modified food caused some reaction in the media and raised some concerns about food safety and the impacts on humans due to the manipulation of genes. Under public pressure, and to gain the public trust, Calgene asked the US Food and Drug Administration (FDA) to approve its first GM product.

Between 1994 and 2004, over 60 genetically modified foods have been approved for sale by Health Canada. In fact, Canadian government officials did not turn down any GM applications that had been submitted during this period. One reason for this may be explained by Health Canada's strict guidelines outlining known requirements for data and protocol related to products used by the industry. Accordingly, if products do not meet the guidelines and criteria, they can not be submitted. In some instances, industry clients withdrew voluntarily before a decision was taken, because their submitted products do not meet Health Canada's strict criteria. (Health Canada, 2004)

There is a fundamental difference in the strategic approach to GM products' safety worldwide. While Canada and the U.S. see all GM products as safe unless proven otherwise (labeling is not mandatory), Europe, on the other hand, sees all GM products as being under suspicion unless proven completely safe, (labeling is mandatory). While in Canada and the U.S., GM food is widely available and accepted by consumers, the European public has kept up its suspicion of GM products. Australia, New Zealand and Japan also maintain labeling standards for GM food products. China is currently a producer of GM cotton and supports the use of the GM technology.

It has been more than a decade since genetically modified foods have been introduced to the food chain around the world. Novel foods, by definition, are foods which are re-processed in a certain way in order to achieve a certain economical, potential or marketing goal. They also refer to products that are not historically proven to be completely safe (Health Canada, 2004). For instance, trans-fat which has been used in many foods, is a product of a food process that creates a better taste, a longer shelf life, and an economically cheaper product compared to the original product. However, studies show that trans-fats are not safe. They could raise levels of LDL-cholesterol, and reduce levels of HDL-cholesterol (Daniells, 2007).

Overall public reaction to genetic engineering remains suspicious. This is the case even though in Canada, nearly all of our food consumed contains GM food products. Faced with a potentially negative public reaction since the public generally does not understand biotechnology, industry leaders appear content to downplay their use of genetic engineering and to blame consumers for not taking to biotechnology because they don't understand it. “Computers have been accepted in our lives, not because we understand how they work, but because they are useful," said Robert Goodman, a biologist at the University of Wisconsin and former executive vice president at Calgene Inc. The biotechnology industry needs to tell consumers "what's in it for them," (Fulmer, 2001).

The Public Health Agency of Canada established an organization in July 2000 to provide Canadians with news, research, and development on pubic health issues in Canada and around the world. This organization is called the Global Public Health Intelligence Network or, simply, GPHIN. Information in GPHIN is useful in understanding the importance of surveillance models (Public Health Agency of Canada, 2004).

The GPHIN acts like an early warning in an internet based system. It collects, organizes, assembles, and distributes significance first-hand information on public health and diseases. Because of its

Internet-based nature, it operates and runs information on a 24/7 basis. By filtering the information in a automated process, only relevant information are released to the Public Health Agency of Canada GPHIN officials for further analysis. By monitoring global public health news via wires and web sites, GPMIN provides important information on disease outbreaks, public health events and news to respond accordingly to rising health risks. Significant information and notifications that may have serious public health consequences are immediately forwarded to users (Public Health Agency of Canada, 2004)

The GPHIN operates as a central coordinating point, and as a nerve centre for public health security in Canada. It helps researchers to identify, reduce, and react to the population's health risks. It creates an effective coordination between different research teams and related private and government organizations, and acts as a centre for disease control programs and population health surveillance. The Public Health Agency's Centre for Emergency Preparedness and Response (CEPR) is in charge of GPHIN (Public Health Agency of Canada, 2004).

GPHIN is a good source and a high ranking network for Health Canada to monitor the occurrence of global health events and international public health news. Any information, such as an early warning of infectious disease outbreaks, drug recalls, food and water safety issues, or even natural and health disasters world-wide are critical tools for post-market surveillance (Public Health Agency of Canada, 2004).

Much research has been conducted, and much information is needed to assure the safety of our foods, drugs and products. Pre-Market Safety and Testing, as well as post-market surveillance, are crucial for systems of control and regulation. The following sections describe the heath, health measurements, as well as the present and future monitoring and surveillance systems in place today.

1.2 Health measurement

"Health", is described by the World Health Organization, as a state, free of disease or infirmity with complete physical and mental well-being (WHO, 1946). Statistics Canada describes "Health measurement" as the analyses and tools to examine directions and patterns of population health. Some of these tools are birth and death rates, as well as health expectancy measures and life expectancy (Statistic Canada, 2007). There are varieties of health measurement tools that are used to track health of populations over time. However, one specific health measurement tool cannot be defined as the "best" tool, since each tool has its strengths and weaknesses (Health measurement Research Group, 2005). Statistics Canada adapted some tools to measure the health state of a population. The following list shows the measures used by the Statistics Canada (2007) fro measuring population health status:

1. Death rates
2. Birth rate
3. Health-adjusted life expectancy
4. Year-equivalents lost to reduced functioning
5. Health expectancy measures
6. Potential years of life lost to a health condition
7. Disability-adjusted life expectancy

The World Health Organization (WHO) has some recommendations for public health measures on disease control. As part of its recommendations, WHO describes public health measures such as coordination of services, vaccination for public health purposes, protection of persons at risk of occupational exposure, personal protective equipment, pharmaceutical treatment to prevent disease, health monitoring, and isolating and managing suspected cases according to recommended procedures for infection control. (WHO, 2005)

The Government of Canada published a report based on comparable health indicators in response to the First Ministers' *Communiqué on health* issued in September 2000. Three years after the report on February 2003, health ministries from the provinces, the territories and the federal government worked together to select and to report on comparable indicators. These health indicators address outcomes of health services, health status, and quality of health services. The committee identifies 14 areas for the indicator reporting: low birth rate, self-reported health, life expectancy, infant mortality, change in life expectancy, improved quality of life, waiting times for key diagnostic and treatment services, patient satisfaction, reduced burden of disease, illness and injury, home and community care services 24 hours a day and seven days a week, hospital re-admission for selected conditions, access to first-contact health services, public health surveillance and protection, and health promotion and disease prevention (Statistic Canada, 2002).

Health Canada in its 2006 federal report, describes comparable health indicators. This report came to improve the First Ministers' Accord on Health Care Renewal report in 2003 that focused on timely subject access, quality, sustainability, and health status and wellness. The 2006 report tries to improve the information on comparable health indicators and to meet criteria for completeness, accuracy and adequate disclosure (Health Canada, 2006b).

The 2006 report also provides information on three main themes of timely access, quality, and sustainability and it focuses on seven specific priority areas under those themes: primary health care, home care, catastrophic drug coverage and pharmaceutical management, diagnostic and medical equipment, health human resources, healthy Canadians, and other programs and services (Health Canada, 2006b).

There are lists of 70 indicators that are developed for public health reporting. The list is available from "A Federal Report on Comparable Health Indicators 2006" (Health Canada, 2006b). However, based on the 2004 report, all federal, provincial and territorial jurisdictions agreed to 18 indicators. The following list shows the 18 indicators: (Health Canada, 2006b)

1-Self-reported difficulty obtaining routine or ongoing health services
2-Self-reported difficulty obtaining health information or advice
3-Self-reported difficulty obtaining immediate care
4-Self-reported prescription drug spending as a percentage of income
5-Self-reported wait times for diagnostic services
6-Hospitalization rate for ambulatory care sensitive conditions
7-Self-reported patient satisfaction with overall health care services
8-Self-reported patient satisfaction with community based care
9-Self-reported patient satisfaction with telephone health line or tele-health services
10-Self-reported patient satisfaction with hospital care
11-Self-reported patient satisfaction with physician care
12-Health adjusted life expectancy (HALE)
13-Prevalence of diabetes
14-Self-reported health
15-Self-reported teenage smoking rates
16-Self-reported physical activity
17-Self-reported immunization for influenza aged 65 plus ("Flu Shot")
18- Body mass index

As it was indicated before, there are many indicators and health measures. There is always a challenge to use the right and appropriate indicators, as well as difficulty to adapt a right methods that can be used for these tools in an effectively and efficiently manner. This thesis will adopt a simple definition that, while recognizing the difficulty of measurement, and complexity of finding appropriate indicators, uses health indicators in an illustrative manner while recognizing the difficulty that such measures entail.

The next section describes how present pre-market surveillance helps monitoring the safety and quality of the population.

1.3 Present Pre-Market Safety and Testing

Health Canada monitors the safety of food production and classifies certain foods either into categories of "safe" or "unknown". As a result, the notion of *novel food* was introduced to consumers. Food and Drug Regulations of the government of Canada has defined a *novel food* as:

(a) a microorganism or a matter that does not have a prior history of safe use as a food;
(b) a genetically modified food such that the plant, animal, or microorganism that exhibits characteristics that were not previously observed in an organic food, derived from a plant, animal or microorganism;
(c) a process that causes the food to undergo a major change that has not been previously applied to that food by means of manufacturing, preparing, preserving or packaging.

(Public Health Agency of Canada, 2004)

As a result of pre-market testing, and as part of the same process used by the Food and Drug Regulation act, a novel food could have the following status:

(a) it could not approved for market consumption;
(b) it could approved unconditionally for the market;
(c) it could approved for the market with some degree of details;
(d) it could be subjected to controlled release with a degree of details;

(Public Health Agency of Canada, 2004)

Health Canada's perspective is to create a fair, efficient, and competitive marketplace for a better, healthy and dynamic economy. The pre-market surveillance and testing is used to achieve an environment of confidence where the public's interests could be protected and the climate for investment, creativity, development, and trust is improved. Both drug and food have pre-market surveillance and safety regulations. The present pre-market testing for drugs in Canada, as described by Health Canada as point-in-time structure, works in a simple framework. For instance, when a manufacturing drug company initially chooses a formula that shows some promise, it has to test it through a development process, initially on non-clinical trials such as with test tubes, animals, and finally on human clinical trials. In the case of any clinical trial (human test trial), an application for approval must be submitted to Health Canada. Once the manufacturer is satisfied that it has enough evidence of a healthy drug and the new drug has the safety, quality, and efficacy for a specific indication, it can file a drug submission to Health Canada. Health Canada reviews applications to see if the application follows the *Food and Drug Act* and its regulations. If it meets all of the requirements, a license will be issued for this new drug, called the Notice of Compliance. As part of pre-market safety regulations, along with issuing the Notice of Compliance, labeling for a food or drug, also must be approved by Health Canada. (Health Canada, 2007)

1.4 Future Pre-Market Safety and Testing

The new Progressive Licensing Framework represents the future in Canada for pre-market testing (Health Canada, 2007). It consists of three parts: (1) a life-cycle (evidence-based approach), (2) good planning, and (3) accountability.

As part of a "life cycle" framework, a food or drug product will be evaluated for its benefit-risk profile throughout its life-cycle. This approach represents a fundamental shift from the previous idea. In the present framework, the safety, and efficacy of a drug is based on pre-market testing. In the future, the drug will also be subject to testing throughout its post-market life-cycle (Health Canada, 2007). The following Figure 1 illustrates the framework for the post-market life-cycle:

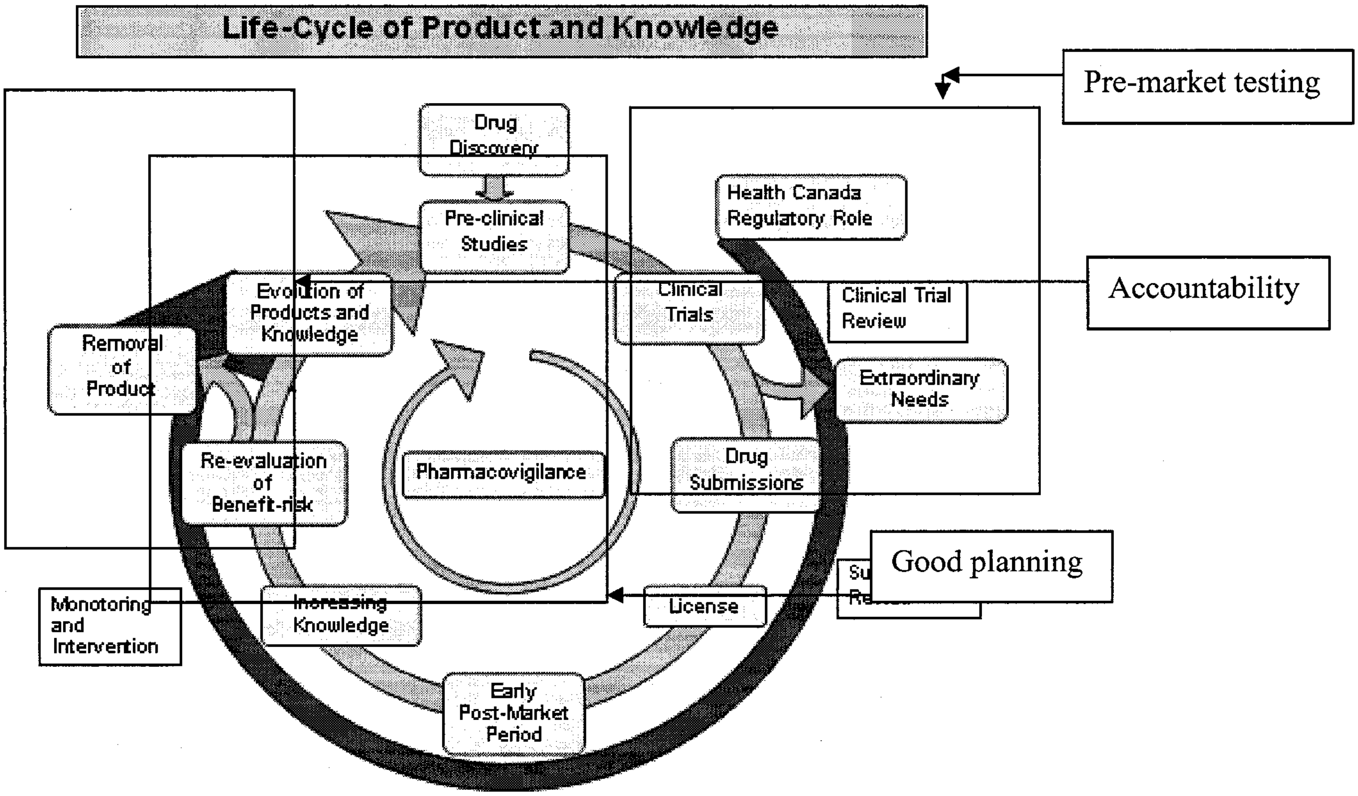


Figure 1: Regulatory framework and critical points in the life-cycle of a drug (Health Canada, 2007)

"Good planning" is another part of this new framework. It suggests that at every step of the regulatory process, a proactive planning approach will be introduced to manage all possible issues related to a new product (Health Canada, 2007).

As part of the "accountability" framework, there will be an on-going requirement to justify the safety and marketing of a food or drug product. As a result, issuing a new license will not act as a green light for complete safety of the product in the post-market period, and adjustments will be done throughout the food or drug product life cycle (Health Canada, 2007).

1.5 Post-Market Surveillance

Post-market Surveillance plays an essential role in market policy. It can act as the public's eyes and awareness. As knowledge is power, both sides, consumers and manufacturers, understand the importance of surveillance and control. Consumers need to be made aware of the safety and health content of products. The manufacturer needs to convince the customers that its products are safe. Further more, post-market surveillance enables us to:

- Evaluate the safety of products in practice over a wide range of consumption
- Verify the effectiveness and efficiency of current policy and control measures
- Provide feedback to the manufacturers, consumers, and the government health agencies
- Protect the health of populations that are presumed to have higher risk

Health Canada understands the importance of health surveillance, and in order to obtain better results, it has created the Global Public Health Intelligent Network, GPHIN with this responsibility.

1.6 Case Study

The case of soybeans demonstrates the market dominance of the public's consumption of GM foods. Soybean is a good example of the positive and negative impacts associated with GM foods.

1.6.1 Soybean

Major world oilseeds come from 7 main sources: soybean, cottonseed, peanut, sunflower seed, canola/rape seed, copra and palm kernel. Soybean plays a major role in oilseed production. In 2005, it was estimated that about 70% of the whole world's oilseed production came from soybeans. (Agriculture and Agri-food Canada, 2005)

Soybean has been produced massively in Canada, the U.S., Argentina, China, Brazil, and many other major agricultural countries worldwide. It plays a critical role in our food chain, as it is a major oil source for our food industry. It is also a good example for the case of GM food. In Canada and the U.S., over 90% of all soybean crops are from genetically modified sources. This is important in order to find out about the percentage of GM uses in overall crop production. In 2004, the cases of soybeans alone, out of 119.5 million acres of GM soybean worldwide, 109 million acres (91%) of GM soybean were produced by Monsanto, a U.S. agricultural company. The same source shows, also in 2004, that Monsanto controlled 25% of the global market share. Again in 2004, according to a study by the U.S. Department of Agriculture, 83% of all soybeans produced in the U.S. were genetically modified (ETC Group Communiqué, 2005).

In 2005, ETC Group Communiqué had a report on the share of GM plants in 2004 around the world. In this report shows the global share in production of GM seeds in 2004:

- USA: 59%
- Argentina 20%
- Canada 6%
- Brazil 6%
- China 5%
- Others 4%

Source: (ETC Group Communiqué, 2005)

A new study in May 2007, by Statistics Canada, shows the total soybean domestic use was 1959 kilo tons (kt) in 2005-2006. Statistics Canada has estimated that this consumption will grow to 2103 kilo tons (kt) in 2006-2007 and 2000 kilo tons (kt) in 2007-2008 (Statistics Canada, 2007). Based on the same source, the soybean production in Canada will grow from 3161 kt in 2005-2006 to 3533 kt in 2006-2007. (Agriculture and Agri-food Canada, 2007)

Figure 2 shows the forecast of soybeans supply and disposition in Canada for 2007 and 2008.

Canada: Soybeans Supply and Disposition
May 29, 2007

Crop Year [a]	2005-2006	2006-2007 [F]	2007-2008 [F]
Seeded Area (kha)	1,176	1,238	1,186
Harvested Area (kha)	1,169	1,226	1,176
Yield (t/ha)	2.70	2.88	2.53
Production (kt)	3,161	3,533	2,975
Imports [b] (kt)	339	250	400
Total Supply (kt)	3,771	4,278	3,950
Exports [c] (kt)	1,316	1,600	1,700
Food & Industrial Use (kt)	1,493	1,475	1,550
Feed, Waste, Dockage (kt)	338	503	350
Total Domestic Use [d] (kt)	1,959	2,103	2,000
Carry-out Stocks (kt)	495	575	250
Average Price [f] $/t	220	250-270	260-300

[a] September – August crop year
[b] Excludes imports of products
[c] Excludes exports of oilseed products
[d] Total Domestic Use = Food and Industrial Use + Feed Waste & Dockage + Seed Use
[e] Soybean food and industrial use is based on data from the Canadian Oilseed Processors Association
[f] Crop year average prices: Soybeans (No. 2, I/S Chatham)
[F] forecast, Agriculture and Agri-Food Canada, May 29, 2007
Source: Statistics Canada, Cereals and Oilseeds Review Series, Cat. No. 22-007

Figure 2: Soybeans Supply and Disposition in Canada (Source: Agriculture and Agri-food Canada, 2007)

As the consumption of soybean increases, the genetically modified food intake by consumers will grow accordingly, since over 90% of all soybean production is genetically modified. At the same time, the overall impact of GM technology for soybean production is uncertain as the following investigations have shown.

One study shows that as a result of inserting a Brazil nut seed storage protein into the soybean chromosomes, some individuals consuming these soybeans respond with an allergic reaction. As a result of this study, this type of genetically modified soybean was pulled from the market (Silbergeld, 2005).

Delegates from 119 countries gathered in Durban, South Africa in 2000 to discuss impacts and usage of GM soybean. Among supportive cases of GM soybeans was that of Almir Rebello, a farmer in Brazil, who showed a significant increase of worms and tiny organisms in his 247 acre farm. This farmer claimed that genetically modified soybeans were responsible for the richness of the soil, which would help to increase production each year (Gobbi, 2000).

Overall, soybeans are an example that there is no conclusive evidence to either prove or reject the safety of such foods. Thus, a mechanism for surveillance and control in the post-market consumption of such foods needs to be implemented and would be a welcome innovation designed to monitor and report on beneficial as well as negative effects.

1.7 Thesis Objectives

This thesis presents a modeling framework for examining observations from post-market consumption surveillance and illustrates a process related to observing and triggering health intervention policies designed to demonstrate how the system could be used to monitor and adapt to hypothetical health impacts. A health intervention strategy design is presented for setting dynamic market policies, based on health status observations from the post-market surveillance observations. This research develops and applies the model to the illustrative case of the decay of population health status attributed to the consumption of complex food products. This example, based on the modern propensity of the population to become more obese, simulates market consumption and market surveillance observations and examines health intervention strategies that are directed to modify health status. Note that this research is focused on the partially observable model design and implementation and does not imply that the relationships between individual consumption and health are known precisely. In summary, the objectives of this research are to:

- Examine market surveillance for consumption of food products such as GM foods;
- Develop a partially observable Markov Chain model with Bayesian updating on the health status of a population for the analysis of post-market surveillance data for monitoring post-market consumption;
- Apply the model to a case study of product consumption and the implied health impacts from consumption by simulating market consumption, surveillance observations, and design and evaluate dynamic strategies for monitoring and controlling aspects of population health.

This thesis develops the modeling methodology to be used for market surveillance and presents a strategy design for setting dynamic market policies given observations from surveillance. Expected results will include direction for an active surveillance system, data collection, analysis and strategy intervention.

1.8 Plan of the Thesis

This thesis introduces a design for post-market surveillance of the partially observable health status of a population. The thesis is presented in six chapters. These are: (1) Introduction, (2) Literature Review, (3) Methodology, (4) Model Illustration, (5) Case Study and (6) Conclusions. In the Introduction presented above, some background information about the pre and post-market surveillance, GM food consumption with their problems and controls, an illustrative case study, and the thesis objectives and the plan of this research was provided. In the Literature Review chapter, the methods of surveillance are reviewed. Chapter 2 analyzes previous work on market surveillance and partially observable systems. In the Methodology chapter, the components of the surveillance model developed in this thesis are described. The model is demonstrated in Chapter 4, in which policy implementation and alarms with system interventions are modelled and discussed in more detail. In Chapter 5, Case Study, the problem of declining health status in an obese population is applied to the original model and the interventions are implied to move the population to an improved health state. In the final chapter, the conclusions of this report and recommendations for future research are presented.

2. Literature Review

A variety of environmental and human health concerns accompany new advances in food and drug consumption introduced to the market. For example, the emergence of genetically modified foods in the marketplace has resulted in a storm of public debate, scientific discussion, political hot topics, and media coverage. This literature review section examines observations regarding market impacts of new foods products such as GM foods and consists of the following sections:

2.1 Market Surveillance

When there is no clear evidence of the health effects connected to new food consumption even after a new food product has been pre-market tested, the uncertainty about potential long-term health effects leads to the need for development of a policy of post-market surveillance. This section examines the notion of post-market surveillance and its discussion in the literature.

2.1.1 What Is Surveillance?

Different definitions or interpretations of the word "Surveillance" have long existed. Related to different jurisdictions, surveillance systems have been used for certain procedures or products. There are many applications for a surveillance system. For instance, Canada has an Injury Surveillance System. In this type of surveillance, information is obtained from all emergency departments in hospitals to keep track of all registered intentional and unintentional injuries incurred by patients. This surveillance provides very high quality data that can be used for different purposes.

The U.S. has used another application for surveillance in a Water Fluoridation Reporting System (WFRS) to create a database for the Center for Disease Control and the Environmental Protection Agency's Safe Drinking Water Information System (SDWIS). (Amanor-Boadu and Amanor-Boadu 2002).

The Canadian Network for Health Surveillance has adopted the following definition of health surveillance:

> "Health surveillance is the tracking and forecasting of any health events or health determinant through the collection of data, and its integration, analysis and interpretation into surveillance products, and the dissemination of those surveillance products to those who need to know." (Health Canada, 2003, p.8)

Health Canada also has defined surveillance as:

> "A more methodological view is that surveillance is the repeated collection of information under an invariant sampling strategy and definitions at constant intervals over a long enough period to enable the detection of changes in a baseline occurrence." (Health Canada, 2003, p.8)

Health surveillance may contain diverse components, models or methods. The following section explains methods that could be used in a health surveillance model.

2.1.2 Approaches to Surveillance

Surveillance can be used for a pre-market and/or post-market case in many different applications. A surveillance system is considered to be a complex system. This is due to the difficulty of finding a balance between the cost, effectiveness solution, and reliability of the surveillance system. In many cases, obtaining accurate data is not an easy task and is considered to be expensive. Moreover, sometimes the information is only partially observable, which is called "Surveillance of a Partially Observable System".

In one of its analysis reports of the post-market surveillance of bio-engineering pharmaceuticals, Health Canada describes the purpose of surveillance as to detect changes in a stable state of occurrence in an object of interest (Health Canada, 2003, p.9). Therefore, the surveillance is rather pattern recognition as compare to hypothesis testing, and a description and not explanation (Health Canada, 2003, p.9). As a result a surveillance analysis does not clearly address cause and effect even though the results are often indicative to an informed analyst. (Health Canada, 2003, p.9)

A complex surveillance system, like any other complex system, requires a careful methodological approach. Health Canada, regarding the same report about the analysis of the post-market surveillance of bio-engineering pharmaceuticals, discusses different approaches to health surveillance. This report categorizes the health surveillance into three approaches: *passive*, *active* and *enhanced* surveillance (Health Canada, 2003).

Passive surveillance is a type of surveillance in which the information is gathered mainly for administration purposes in a generalized form of information through a second or third party, and is usually cheap to operate. Active surveillance is used in a standardized manner, using a faster and higher quality method of data collection. Enhanced surveillance has no fixed design, however it uses superior testing, improves structure and strength, and is more costly than the other methods. These three types of surveillances are described in more detail below.

2.1.3 Passive Surveillance

Passive surveillance is used more often in the case of health surveillance, compared to the other types of surveillance such as active and enhanced. The passive surveillance information is often collected for hospital administration rather then clinical or academic research. For instance, the information is more often used for clinical billing or hospital admission/discharge. As a result, the data have fewer details and their quality is lower. Consequently, data from passive surveillance is not very reliable for research purposes.

> "Typically, these datasets contain little richness or detail relevant to surveillance of health status to begin with. Further, the records abstracted for surveillance purposes are usually anonymized and have been through a number of edits which might categorize discrete values, impute missing values and generally act to degrade the information value of the original data." (Health Canada, 2003, p.9)

Although, passive surveillance has some key advantages compared to other surveillance methods, such as being relatively easy to implement and cheap to operate, their usefulness in a post-market context is highly problematic. One of the main disadvantages of passive surveillance is that its data are often dated, e.g., available only once a year. For that reason some systems, such as the surveillance of infectious diseases where a rapid response and the need for fresh data are required, passive data are not effective. (Health Canada, 2003)

2.1.4 Active Surveillance

Active surveillance systems are administered in a standardized manner. They use purpose-designed data collection tools, allowing much faster time to analyze the elapsed time between events. This approach gives active surveillance some major advantages over passive surveillance systems. While in passive surveillance the elapsed time may be more than a year, in active surveillance it is in a matter of hours or a few days. Another advantage of active surveillance, compared to passive, is the quality of the data. Collected information in the active surveillance approach often passes through fewer hands between collection and analysis. Therefore, the data are of a higher quality of more relevant information, regularly available in a short period of time. The main disadvantage of using active surveillance is its applicable cost of design and operation. This is also the reason why there are relatively more passive surveillance systems in comparison to active systems. (Health Canada, 2003)

2.1.5 Enhanced Surveillance

Enhanced surveillance is based on having no fixed design, as compared to active or passive. Enhanced surveillance generally follows the active surveillance approach and increases the limitation on data-collection based on any possible relevant information that can be collected. Health Canada defines enhanced surveillance as a method of data collection on risk factors.

> "Enhanced surveillance generally extends the approach of active surveillance to include data collection on risk factors, exposures, and other information thought to have relevance." (Health Canada, 2003, p.11)

This approach supports types of analysis which are believed to be beyond recognition of a traditional surveillance-type pattern. The fact that enhanced surveillance changes the face of traditional surveillance into multivariable hypotheses testing is attractive. However, it has a major disadvantage, which is its high cost. In practice, the usage of enhanced surveillance methods is limited.

In comparison, Health Canada concludes that even though the passive approach is relatively easy to implement and cheap to operate, its degree of error and uncertainty, and slow information generation are highly problematic for post-market surveillance. The enhanced surveillance has the advantage of extending classic surveillance into multivariable hypothesis testing. This surveillance can be more useful for health surveillance or particularly in purely disease oriented surveillance. However, it has a high cost for implementation and therefore is limited to certain cases. Active surveillance provides a reasonable potential and is a logical choice for post-market surveillance.

As it was described before, some systems are only partially observable. This is due to their complexity and partial accessibility to their information. In the case of surveillance of partially observable systems, the obtention of complete data is considered to be difficult and/or costly. The next section describes health surveillance in partially observable systems.

In the case of health, it is important to perform basic surveillance on defined health outcomes along with the monitoring of the consumption item in the marketplace. What we are looking for is a better understanding of the impacts of consumption on public health through observation, using post-market surveillance. Yet, for GM foods products fro example, there is no known operational post-market surveillance system.

The health Canada, in its 2004 report, concludes that at the present time it is not realistic for a generalized surveillance to provide meaningful data on the linkage between consumption of GM foods and health outcomes (Health Canada, 2004, p.12). However, for a test specific risk hypotheses a post-market monitoring would provide important information (Health Canada, 2004, p.12). This report concludes that there is no operational post-market surveillance system for GM foods internationally (Health Canada, 2004, p.12).

2.1.6 Consumer concerns

In October 2002, Finlay and Sheeshka (2002) from the University of Guelph released their research on post-Market surveillance of GM foods and consumer concerns. They conducted a simple survey by asking a group of people to associate freely the first three words or phrases that come to their mind when they think of GM foods. The questionnaire had a scale ranging from very positive (+1) to very negative (+5). There were four separate questionnaire sections: Risk ratings of GM and 16 other technologies, acceptability of 9 different applications of GM, a knowledge questionnaire and finally demographic information. The results include the following table:

Question	% of Respondents Mentioning	Rating
Mentions of fruits and vegetables	34%	2.97
Are GM foods natural?	29%	4.07
Mention about technology	19%	3.13
Questioning safety and risk	17%	3.81
Positive consequences of Gm foods	12%	2.17
Chemicals/hormones	12%	3.91
Rating: 1 = positive .....5 = very negative	Source: Finlay and Sheeshka, 2002	

Table 1: Survey on customers' concern about GM foods

Finlay and Sheeshka reported the perceptions of risks versus benefits: the average of 3.92 (rate) think benefits slightly outweighs risk. In this rating, as it is shown on the Table (1), the value of 1 represent a "positive" rating, and thus the benefits are measured with low numbers. The risk being more negative with high numbers; for instance a value such as 3.92 is much larger than 2.5 and is therefore "negative.

In this survey, Parents rate risks as outweighing benefits. College education rate benefits over risk. On the question of Safety of GM foods the following responses were found:

1) Average response rating was 2.69 - slightly closer to disagree
2) 50% responded that they strongly disagree or disagree
3) 40% responded that they strongly agree or agree
4) 7% responded that they neither agree nor disagree
5) Slightly more parents disagreed that GM foods are safe

Finally, they reported that Parents with children are significantly less supportive on the issue of support for GM foods, while the university educated parents are less supportive. This survey reports that 69% said that on the issue of purchasing GM Foods, if they had a choice, would stick with the foods they are currently buying (Finlay & Sheeshka, 2002, p.11). This report suggests that participants of purchasing GM foods' survey were divided into 2 subgroups: "Health and Price-Sensitive" and "Knowledge Conscious" (Finlay & Sheeshka, 2002, p.11).

Despite the lack of evidence in one direction or the other, the study demonstrates the relative uncertainty of consumers' perceptions regarding GM foods. Thus, this study demonstrates the need for post-market monitoring of the impacts of consuming GM foods. As such, post-market surveillance is increasingly required by some regulatory authorities for the marketing approval of GM Foods and drugs (J. -M. Wal, P. A. Hepburn, L. J. Lea and R. W. R. Crevel . July 2004, pages 98-104). This requirement aims to show that unexpected effects do not occur after long-term everyday exposure. Large food manufacturers have passive systems to obtain feedback from consumers on their products, e.g., adding a contact email or 1-800 phone number for comments and feedbacks from their consumers on the product's package. Such feedback and surveillance systems can be enhanced to collect information on possible adverse health effects of specific products and relate these to intake in specific groups of consumers. Examples of surveillance applications products are described in Section 2.3 below.

2.2 Partially Observable System Analysis

In a partially observable system, monitoring the system yields only a probabilistic view of the actual state of the system. It is impossible to obtain complete information in all sub-systems of a partially observed system due to the inability of the surveillance system to observe all elements of the population. Monitoring the consumption patterns and health effects of GM foods products in a population yields is complex and the interactions between consumption and health impacts are not well-defined. Thus, observations from the surveillance system are only partially informative about the health impacts and health status of the system. Baynton describes some main reasons for calling a GM system partially observable.

> "Taken together with variation in diets and dietary components, genetic variability within a population that affect individual predisposition to possible adverse food related effects, and other environmental factors unrelated to diet, it is unlikely that observational studies would uncover any health effects due to the GM nature of food." (Baynton, 2002, p.65)

Post-market surveillance of GM foods therefore has limited information. This is due to the lack of complete information and access to all individuals who have consumed such products or foods.

> "The feasibility of undertaking epidemiological studies to assess any post-marketing effects of GM foods on human health aspects appears to be limited. No reasonable firm hypotheses about which human health end-points GM foods might affect. Individual exposure to GM foods is likely to be difficult to access." (Baynton, 2002. p.65)

Applications of the analysis of partially observable systems outside of the health system do provide insight into modeling mechanisms that may address the consumption-health impacts problem. For example, an application of a partially observable system for assessing resource stock status was presented Lane(1989). The paper presents an application of a Markov decision process for the partially observable model of decision-making by fishermen. Throughout each fishing season, independent boat and vessel operators must decide which area or fishing ground of the fishery to fish during each period. They must determine in which zone to catch the most fish with the highest return to fishing effort. Fishermen's decisions are assumed to be made to maximize net operating income. This decision model uses the data from the cost of the fishing effort, the unit price of fish and the potential fish catch. The model helps understand the rational behavior and decision-making processes of fishermen.

> "The decision model incorporates the potential fish catch, the cost of the fishing effort, and the unit price of fish. Catch potential is modeled by considering the abundance of the fish stock and the ability to catch the fishing technique. Abundance dynamics not observed directly are modeled as a Markov chain with a state-space representation. Dynamic decision policies are computed by the method of optimal control of the process over a finite horizon. The resultant policies are used to simulate distributions of fishermen's net operating income, fishing effort dynamics, and catch statistics. The model may be used as a decision aid in the regulation of the common property fisheries resource" (Lane, 1989).

Another application of a partially observable system is on decision-making in a multi-agent system with some unknown information, using Markov decision processes. In multi-agent systems, decision-making and selecting a strategy are the key performance components. This can be a challenge if the system is partially observable, since for strategy selection it is required to have a certain amount of information. In this case, a method with some implementation samples is used to employ a bi-simulation over information of the model to collapse the structures at each time step, using expected values of variables in a probabilistic Kripke structure (Nicholson, 2002). Bi-simulation is a common behavior in simulation between some state transition systems, where one system simulates the other and vice-versa. It acts and behaves in an equivalence relation between state transition systems and associating systems.

Management of patients with ischemic (lack of blood) heart disease, diagnosis of their diseases, and their treatments is another application of a partially observable system. The problems of uncertainty about the underlying disease, uncertainty associated with the patients' response to the treatment, cost-decision of a different diagnostic method, and treatment procedures are associated with this type of the partially observable application. To tackle those problems, related to modeling of such a complex decision process, a partially observable Markov decision process (POMDP) framework is used (Hauskrecht and Fraser 1998).

One of the most important applications of the partially observable system is in health care system. Canada spends billions of dollars in health care system to solve the problems with health care efficiencies. The UBC Center for Health Care Management reports from the Mathematics of Information Technology and Complex Systems (MITACS), a network for the Mathematical Sciences, that Canada has the largest industry in health care with more than $140 billion spending budget:

> "Health care is Canada's largest industry with expenditures exceeding $140 billion. The Canadian healthcare system is at a critical point; it faces an aging population, attrition in its workforce and pressure to adopt new and costly technologies. Further, long current wait times for health care services has become one of the paramount issues facing Canadians. To meet these challenges, health system leaders and managers require analytical models to support their system efficiency and capacity investments decisions." (MITACS-a, 2006)

For instance, HIV treatment planning to consider patient devotion to therapies uses a POMDP model to solve the health care efficiencies issues in this partially observable system. The imperfect devotion or adherence in HIV care is a major problem, because even an ordinary absence from perfect support may result in significantly reduced benefits of therapy. Although significant research is being done to improve patient behavior for the treatment, it is also important to consider some best possible treatment models for patient adherence. Difficulty to measure the patient devotion, ambiguity of the subject, and the difficulty of testament's accuracy propose the use of partially observable Markov decision process models. (MITACS-b, 2006)

These POMDP applications show us how to apply a similar method for the cases of partially observable systems in postmarket consumption and partrially observable health effects. The cases of

GM foods have raised safety concerns while crossing traditional boundaries between producers and consumers. Although consumers are looking particularly for a low-price, convenient, and diverse food products, they are also demanding for high quality, reliability and safety standards of such products. The safety of GM foods has always been a controversial issue, and since these products are partially observable, it requires a reliable method for their surveillances. The following section describes research by Finlay and Sheeshka (2002) from the University of Guelph, on consumers' perspectives on trust in government and post-market surveillance of genetically–modified foods.

2.3 Surveillance Applications

There are many applications of surveillance as a mean of monitoring and controlling a new product, food or drug. In this section, surveillance applications are illustrated. These applications include: monitoring vaccines, monitoring medical devices, comparative testing on biosimilars, monitoring risk assessment and management of occupational exposure to pesticides in agriculture.

2.3.1 Post-market surveillance in monitoring vaccines

Post-market surveillance is used for the safety monitoring of vaccines in Germany. In this surveillance system, after vaccination, all reported suspected adverse drug reactions (ADR) are collected into a database at the Paul Ehrlich Institute for a safety monitoring of a vaccine. According to the German Drug Law and European Regulation, pharmaceutical manufacturers and all marketing authorization holders have the legal obligation to report suspected adverse drug reactions to the authorities. Also, physicians are obligated to report to the German Infection Protection any suspected cases of complications after immunizations. (Weisser et al, 2007).

Vaccine surveillance was conducted during 2004 and 2005 in Germany. In the observations, infants and young children (0-2 years), were the age groups with the highest absolute number of reported cases (two thirds), and adults (18-59 years) accounting close to one third in each of the annual reports. The following data shows the results for this vaccine surveillance in 2004 and 2005:

(1) Total number of suspected complications after immunizations or suspected cases of adverse drug reactions: 1393 in 2005 as to 1273 in 2004.

(2) Serious adverse drug reactions (ADR): 919 (66%) in 2005 as to 858 (69%) in 2004

(3) Reported ADR cases by physicians: 517 (37%) in 2005 as to 414 (33%) in 2004

(4) Reported of reaction to be serious: 229 (44%) in 2005 as to 251 (61%) in 2004

An indicator that was used by the German market during the observation period shows the total number of reports divided by the total number of vaccine doses was 3 reports per 100,000 vaccine doses.

2.3.2 Post-market surveillance in monitoring medical devices

The Education Department, FIMP Lombardy, Italy, showed how a post-market surveillance was used to assess the safety, effectiveness and parental compliance with a medical device. The monitoring was applied to a device that worked for the removing excess nasal concealment by suction in babies viral infections of the upper respiratory tract. In this method, post-marketing and customer satisfaction surveillance was performed in a prospective observational non-comparative cohort study. In this surveillance, 240 patients took part in the safety assessment and 212 went under clinical efficacy assessment. By comparing two examination forms, one for before, and one for after using the medical device for the treatment, the input data were analyzed. The result showed that 68% of parents reported that the device was simple to use, and 86% judged this device to be more effective than other similar devices. The surveillance report showed progressive improvement in the children's' conditions during the treatment period and an extreme satisfaction of the babies' parents with the effect of using this device (Casati et al 2007).

2.3.3 Post-market surveillance in monitoring exposure to pesticides in agriculture

An article by the department of Occupational Health in the University of Milan presents a study of post-market surveillance in agriculture that was used to monitor the effect of pesticides, fertilizers, and chemical toxics used in agriculture, on the health of labourers and farmers. As in most countries, a specific and complex legislation prescribes an extremely careful risk assessment process for pesticides prior to their entrance to the market. A post-marketing risk assessment helps to assess the risk during the use of pesticides. The results of the pre and post-marketing risk assessment are the basis for the health surveillance of exposed agricultural labour force to pesticides. This research concludes that administrating, managing and, assessing the health risk caused by pesticides in agriculture is a complex and essential task, the experience has shown that prevention of health risk caused by pesticides is technically feasible and economically rewarding (Maroni et al 2006).

2.3.4 Post-market surveillance in comparative testing on biosimilars

Biosimilars, also known as "follow-on biopharmaceuticals" in the U.S.A., are unlike traditional pharmaceuticals. Their aim is to copy a complex three-dimensional protein structure with high molecular weight. Any small error or altering in the process can change the product effect and its safety. The quality, safety and efficacy of the reference product will depend on an extensive comparability testing. The European Agency for the Evaluation of Medicinal products (EMEA), according to its guidelines, demands a demonstration to show comparability of the biosimilar products' profile as the reference product. Although various analytical examinations are available to compare a potentially similar biopharmaceutical with a reference product, it is important to recognize the limits of such existing analysis and examination. The application proposes that post-market surveillance can actively examine comparability and similarity of a biosimilar product to a reference drug. This can be done by examination of the quality and limits of such analytical methods. The method requires the reliable testing of the protein content, stability, activity, impurities, physiochemical integrity, and its other additional chemical components. There are challenges in this surveillance method, since it is difficult to achieve an international standard to resolve the differences in methods and materials from laboratories. The article suggests that clinical trials are important to guarantee the product's safety and efficacy over time (Locatelli and Roger 2006).

2.3.5 Post-market Surveillance in genetically modified crops

Although usage of gene recombinant technologies has helped agriculture industry improve production, there is always an unknown risk attached to the consumption of genetically modified crops. International organizations, such as FAO, WHO and OECD believe that the safety of transgenic crops should be carefully and completely evaluated. They have reached a common agreement that the evolution should be based on the substantial similarity principal on toxic tests, substantial equivalent analysis, protein allergenic study, and nutritional assessment. In addition to these international organizations, the European Union (EU) has also recently adopted legislation on the cultivation of GM crops. Based on this legislation, it is required to have post-market surveillance for any unanticipated contrary effects of GM crops in the long term. This strict strategy can help the safety assessments of GM crops (Zhuo and Yang 2005).

2.3.6 Applications of Surveillance of GM Foods

Although the U.S. government does not have a post-market surveillance or monitoring system for bio-engineered foods, the Food and Drug Administration (FDA) is responsible for monitoring of all foods including bio-engineered foods. The surveillance of GMOs (genetically modified organisms) is part of the FDA's responsibility in the U.S.

> "GMOs (genetically modified organisms) were created to enable plants to grow quicker and produce a greater yield/harvest for the production of food while using fewer pesticides. Approximately 70% of processed foods have genetically modified ingredients, yet most are not labeled as genetically modified. For the first time in human history, corporate scientists are using technology to introduce

the genes of one type of food into another. Some of the GMOs to watch out for are: Soybeans, A third of Corn (maize, cornmeal), Ketchup, Cake mixes, Potatoes, Squash, Tomatoes, Corn flakes, Crispy tacos, Cheese pizzas. Organic foods and unprocessed, whole food items are less likely to be genetically modified." (Hull, 2007)

StarLink Corn is an example, where a surveillance of GM food was conducted by the FDA. The first news about GM StarLink corn hit world headlines in 2000 (Agrifood Awareness Australia, 2001). It was not long after StarLink corn initially was approved as an animal feed, that it was found in most supermarket products through the U.S. "StarLink corn seed was registered and annually renewed for domestic animal feed and non-food, industrial use in the U.S. in 1998, 1999 and 2000" (StarLink, 2001).

> "StarLink corn was genetically modified to resist major corn pests. It contains a soil bacteria gene from the *Bacillus thuringiensis* (Bt) family, which allows it to produce an insecticide protein (Cry9C) which controls major corn pests such as the European corn borer and the Southwestern corn borer." (Agrifood Awareness Australia, 2001, p.1)

Even though, there was no evidence that StarLink was harmful to human health it was recalled from the market in 2000, followed by a multi-million dollars loss in markets. In 2000, an environmental group tested supermarket corn products for traces of StarLink corn. They found its genetic material in taco shells. In 2001, StarLink Limited Inc. opened a claims line and a 1-800 number for farmers to fill out an application for their claims (StarLink, 2001). The FDA conducted a post-market surveillance of consumers' complaint reports and discovered that they may be related to possible allergic reactions to the protein in StarLink corn.

There are other similar cases for applications of surveillance of GM foods. For Instance, Becel Pro-Active margarine was allowed to carry the Heart Foundation's logo for several months while the foundation was receiving commission from its sales (Kleter et al 2001). Becel Pro-Active margarine contained a product called "linola", a linseed modified to have an oil composition like sunflower seeds through a mutation or change in genetic material work. Therefore, it was treated as a genetically modified food (Keller 2002).

In 2001, Health Canada decided to pull Becel Pro-Active, a fat spread made with added phytosterols, from stores and issued an advisory statement, considering Becel Pro-Active to be unsafe. In its statement, the Health Canada says that the product was not in compliance with the Canadian Food and Drugs Act and concerned that phytosterols may pose health risks for certain groups, such as pregnant women, and children and/or people on cholesterol-lowering medication. (Gondziola and Badger, 2005)

In the next chapter, the methodology and design for the quantitative analysis of consumption and post-market surveillance are presented.

3. Methodology

This chapter presents the methodology and model design for setting dynamic market policies given observations from the post-market surveillance of a consumer product. The method provides a probabilistic model framework for analyzing market observations and post-market surveillance of consumer products including for example, market approved GM foods, drugs, etc., that are often noted as having unknown post-market performance.

3.1 Problem Definition

The problems this model addresses include the absence of a reliable post-market surveillance model for a system that is only partially observable and post-market performance of consumer products of interest is uncertain. ,Such products include for example GM foods and the case of uncertain health performance on the population as a whole for consumer products that have been pre-market approved..

The objectives of this section are to provide a generic post-market surveillance model for partially observable health performance systems, and to use the models to estimate the indication of the true health status of the population through observations from an active surveillance system

3.2 Model Input Data and Information

A reliable and accurate surveillance model requires an accurate input data base. The input information of the surveillance model assumes the availability of the collection of data in the following categories:

- Identification of a specific consumer product that has been pre-market approved including its distribution and consumption to the population or local subpopulation

- Identification of a specific population segment of product consumers over a defined period of time
- Estimation of the impact of consumption of consumer product and its influence on the health of the population segment under investigation over the planning period
- Impact of alternative health policy interventions on population health, e.g., restriction of consumption of the product to subpopulation units who are not judged to be at risk

These data are assumed elements for the development of the surveillance model and the evaluation of alternative policy interventions designed to maintain and improve the population health status. In this thesis, the availability of these data are taken as given. Actual data associated with illustrative examples are not expressly collected. As such, the assumed data are used to show the development and application of the partially observable system model.

3.3 The Model

The backbone and skeleton of this surveillance model is based on the known methods of Markov Chains and Bayes' theorem. These methods are used to generate, estimate, and repeatedly re-estimate probability distributions of random variables of interest, e.g., the overall health status of a population that is consuming a product of interest in post-market surveillance.

3.3.1 Bayes' Theorem

Information about the estimated and partially observed health status of a population of interest is the end result of the surveillance model. In this model, Bayes' theorem is applied to translate the observed information about health status into an updated probability description of the health status for the entire population. By using the Bayes' theorem, the health status of the population after each observation is re-estimated using a conditional probability distribution of the health state and health observation information.

Bayes' theory is named for Thomas Bayes (1702-1761). Bayes' theorem is based on conditional probability distributions of random variables. It suggests how to update or to revise events and to state their relationships.

The Thomas Bayes' theory was published after his death by his friend in 1967. When the Bayes theorem is being stated mathematically, it has an uncontroversial and simple result in probability theory. However, appropriate uses of this theorem in specific cases have been the subject of continued controversy. (Spiegelhalter et al, 2004)

David J. Spiegelhalter, Keith R. Abrams, and Jonathan P. Myles define a Bayesian approach in their book "Bayesian Approaches to Clinical Trails and Health-Care Evaluation", as the explicit use of external evidence in analysis, monitoring, design, explanation and reporting of a health care evaluation. They argue that such a perspective can be more flexible than traditional methods, because it can adapt to each unique situation. It can be more efficient, because it uses all available evidence. It's more useful, because it provides predictions and inputs for making decisions for specific patients, or for public policy, or for planning research. It can be also ethical in both fully take advantage of the experiences provided by past patients and clarifying the basis for randomization. (Spiegelhalter et al, 2004)

Consider two separate events A and B that may occur within a base sample space. Bayesian updating is based on considering the joint probability of both events, A and B, occurring together. While performing an arithmetic operation on the probability of the relationship between A and B, an updated estimate of a base probability statement will be provided (Annis, 2007).

The conditional event probability Pr (**A|B**) is an *Updated probability* of seeing event A given that event B has already happened (Annis, 2007), where:

Pr (**A**) = is the probability that event **A** is going to happen,
Pr (**B**) = is the probability that event **B** is going to happen,
Pr (**A|B**) = is the conditional probability of **A** happening, given **B** has occurred,
Pr (**A** and **B**) is their joint probability (Annis, 2007), and Bayes' theorem is written as:

$$\Pr(\mathbf{A}|\mathbf{B}) \times \Pr(\mathbf{B}) = \Pr(\mathbf{A} \text{ and } \mathbf{B}) = \Pr(\mathbf{B}|\mathbf{A}) \times \Pr(\mathbf{A}) \tag{1}$$

Therefore:

$$\Pr(\mathbf{A}|\mathbf{B}) = \Pr(\mathbf{A} \text{ and } \mathbf{B}) / \Pr(\mathbf{B}) \tag{2}$$

So, the result can be derived as:

$$\Pr(A|B) = \Pr(B|A) \times \Pr(A) / \Pr(B) \tag{3}$$

By knowing the above mathematical properties of the probability, the following rules can be concluded: “”

$$\Pr(A \text{ and } B) = \Pr(B \text{ and } A) \tag{4}$$

Considering this rule and rule that was expressed in equation (3), we can conclude:

$$\Pr(B|A) = \Pr(A|B) / \Pr(A) \times \Pr(B) \tag{5}$$

This result explains how an initial probability Pr(B) is changed into a conditional probability Pr(B|A) when taking into account the event A or Pr(A) is occurring.

Using the same theory, another conclusion can be driven so that

$$\Pr(B^\wedge|A) = \Pr(A|B^\wedge) / \Pr(A) \times \Pr(B^\wedge) \tag{6}$$

where B^ represents the event “not B”. Similarly the following equation can be obtained:

$$\Pr(B|A) / \Pr(B^\wedge|A) = \Pr(A|B) / \Pr(A|B^\wedge) \times \Pr(B) / \Pr(B^\wedge) \tag{7}$$

Those above equations show how Bayes theorem adepts and accomplishes those transformation without even calculating Pr(A). This is a fundamental of a Bayes theorem (Spiegelhalter et al, 2004).

3.3.2 Markov Chain

A Markov Chain is a mathematical description, based on a discrete-time random process, named after Russian mathematician Andrey Andreyevich Markov (1856-1922). In Markov Chains, the system's state may change to another state in a unit time, or it may remain in the same state. These changes of state, which are described in the form of discrete state matrices, are called state transitions. The Markov property is a term to define a sequence of states, such that the future transition of a given current state is conditionally independent of its prior states.

Assume that the sequence of X1, X2, X3,…is a Markov property random variable then the first order Markov Chain obeys the condition:

$$\Pr (X_{t+1} = x \mid X_t = x_t, \ldots, X_1 = x_1) = \Pr (X_{t+1} = x \mid X_t = x_t) \qquad (8)$$

where, the probability of the future state in the successive period t+1, Xt+1, depends only on the current state of the system, Xt and is independent of its history. In this thesis, the first-order Markov Chain property is assumed to apply to the transitions of the population's health state in the surveillance of the partially observable system, i.e., the transition of the population health state in the successive period depends only on the current health state.

3.4 The Model Components

Consider that a given population consumes a consumer product or class of products that may affect its health status, e.g., GM foods, in some undetermined way. Consider that the product has been already pre-market tested and approved for the marketplace. Market exposure and consumption could affect different segments of the populations in different ways. For example, the population is considered to be comprised of populations of the young, the elderly, children, males and females.

The post-market surveillance model examines the impact on a population of consumers by observing the expected impacts on the health status of the population in conjunction with the consumption of the products of interest. The model monitors the population health and seeks to attribute the benefits and costs of consumption to the new market product. As such, the information from population health observations are designed to assist in understanding post-market health impacts and, thereby to direct market policy for the consumption of the product. For example, if a group of GM food products are observed to not realize benefits for some segment of the population, then a revised market protocol might consider restricting the consumption of foods by this segment as an adopted health improvement policy.

It is understood that the actual link between consumer products, consumption, and health status is complex. It should be noted therefore that this thesis does not make a direct link between product consumption and health. However, it is assumed under idealized conditions that ceteris paribus, health performance change may be indirectly attributed to product consumption in the population as a whole.

Assuming the above linkages, the following subsections identify the particular model components. These include:

1) State definitions
2) Dynamic transitions
3) Observations and
4) Reliability indicators

These model components are discussed in more detail below.

3.4.1 States

Let the vector **S**(t) denote the health status of a consumer's population at time *t*. Let Si, i =1,2,3,4,5, denote each element of the vector, to indicate one set of discrete "health outcome" states attributed to the population of interest. The health status of the population at time *t* (prior to the introduction of the consumer product) is initially described by a prior probability distribution on the states of health from an "excellent" state of health, S1 to a "very poor" state health, S5, as follows: Pr{Si (t)} = Probability that the population is in health status i, for i=1,2,3,4,5.

Let S1 denote "Excellent" population health status; let S2 denote "Good" health status; let S3 denote "Acceptable" health status; let S4 denotes "Poor" health status; and let S5 denote "Very poor" health status. For example, let the initial probability distribution of the health status be given by P{S(t)}:

$$\Pr\{S\ (t)\} = (0.2, 0.4, 0.2, 0.15, 0.05)\ (t) \tag{9}$$

By considering the whole population to be described generally as being in only one health state at time t, then this vector represents the probability distribution of the population's health outcome at time t. It describes that there is a 20% probability that the subpopulation is in excellent condition, 40% probability of being in a good condition, 20% probability of being in an acceptable condition, 15 % probability of being in a poor condition, and 5% probability of a very poor or sick condition for this population.

3.4.2 Dynamic Transitions

To observe the effect of the consumer product on the health status of the population, the population is surveyed, using measures that provide a partial observation or sample of the health status of the population in each period. Furthermore, it is assumed that the health status of the population changes dynamically as a function of the population's current health status and the passage of a single time period.

It is also assumed that we have pre-market information about the population's health status and under this assumption we can provide a summary of the initial population's health status before the introduction of the consumer products into the consumer market system. Subsequent observations about the population's health allow us to update our estimate of the overall health status of the population. The goal is to observe the positive or negative impact on the health status in conjunction with the market availability of the consumer products. If the market availability of the products are revised and the health status changes beyond what was expected from a probabilistic perspective, then there may be said to be a link between consumption change and overall population health status adjustment. In this way, product consumption interventions may be devised to impact the population health.

The surveillance system monitors the observations and the updates health status statistics. Changes to health status may trigger policy intervention if the health status probability estimates for given states for example exceed a preset boundary protocol. For example, if the estimated health status deteriorates due to the consumption of the consumer products, then a new protocol restricting market availability could be applied, thus influencing a potential change in the health status transitions of the whole population.

Define the period-over-period state probability transition matrix, **Pt**, in which for each time period, t, of the planning period, the population health status in time t depends on its state in time t-1, as per the first-order Markov property assuned. For example, the matrix **Pt** below defines the period-over-period state probability transition matrix as:

Pt =

Transition Matrix

		S1	S2	S3	S4	S5
	From/To	**Excellent**	**Good**	**Acceptable**	**Poor**	**Very Poor**
S1	**Excellent**	0.45	0.3	0.15	0.075	0.025
S2	**Good**	0.2	0.45	0.2	0.1	0.05
S3	**Acceptable**	0.1	0.15	0.45	0.2	0.1
S4	**Poor**	0.05	0.05	0.15	0.45	0.3
S5	**Very Poor**	0.025	0.075	0.15	0.25	0.5

Table 2: Period-over-period state probability transition matrix

For instance, the health status of the population currently in state S3 has a 45% probability of staying in this same state after one period.

3.4.3 Observation

Assume that the health status of the population can be partially observed from a surveillance sampling system in each time period, t. Sample observations cannot reveal the actual health status of the whole population, but yields only partial information about the true state of the health status of the overall population resulting in a probability vector over the health states. Assume that the observed evidence gained by surveillance is a discrete variable, Oj(t), j=1,2,3,...k which can take on one of a discrete set of possible observation values at time *t*, $\{O_1, O_2, \ldots, O_k\}(t)$.

The information about the actual health status of a sub-population is required to be reliable, reputable, verifiable and a regularly accessible source. Finding such a source is a major issue for the surveillance of a partially observable system. As noted above, obtaining information about population health status is not an easy task. For instance, there are problems with obtaining accurate and reliable information because data are often incomplete and fragmented.

Another problem is that the results of research are not easily available to Canadians. This issue was pointed out by the National Task Force in 1991 (Statistics Canada, 2007b). The problems involved in gathering information initiated a move by the Canadian Institute for Health Information (CIHI), Statistics Canada and Health Canada to join forces to create a National Health Information Roadmap. (Statistics Canada, 2005a)

CIHI, Statistics Canada and Health Canada use health condition, human function, well-being, and deaths as their indicators for evaluating population health status. They use continuity, effectiveness, efficiency and safety indicators to describe health system performance (Statistics Canada, 2005a). The Canadian Health Information Roadmap Initiative (CHIRI), the Canadian Population Health Initiative (CPHI), the Canadian Institutes of Health Research (CIHR), and the Canadian Institute for Advanced Research (CIAR) are some examples of such those resource centers for a Canadian post-market surveillance model (Public Health Agency of Canada, 2002).

3.4.4 Reliability Matrix

The reliability matrix provides probability distributions for describing the observations about health status that may occur assuming that the population is actually in a particular health status. Let reliability matrix, R, represent the reliability of the state-to-observation probabilities, e.g.,

Reliability Matrix

R =

		O1	O2	O3	O4	O5	Total
S1	Excellent	0.4	0.3	0.15	0.1	0.05	1
S2	Good	0.3	0.3	0.2	0.1	0.1	1
S3	Acceptable	0.1	0.2	0.4	0.2	0.1	1
S4	Poor	0.07	0.1	0.28	0.3	0.25	1
S5	Very Poor	0.03	0.1	0.17	0.3	0.4	1

Table 3: Sample reliability matrix

R is a conditional probability matrix, called the reliability matrix. Given a true statement of the actual health status, Si, the rows of R represent the probability distribution across the discrete observation possibilities, e.g., assuming that the population is actually in state S3, then there is a 10% probability that O1 will occur as the health status observation from the population sample.

3.5 Sufficient Statistic Model

This section exhibits a general description of the model process and dynamics.

As noted above in equation (5), Si(t) denotes the ith element of the health status at time t. The probability distribution, P{Si(t)} is the probability that the population is in state Si at time t. By Bayes' theory, P{Si(t)|Ot} is the conditional probability of Si(t), given Ot, or in other words, it is the probability that the health status element Si(t) is going to happen, given that information and history about the health status is being obtained from the observation Ot. Consequently:

$$\mathbf{Pr\ \{Si\ (t+1)\ |Ot\} = Pr\ \{Si\ (t+1)\ and\ Ot\}\ /\ Pr\ (Ot)} \qquad (10)$$

Pt is the probability transition matrix (Period-over-period matrix) and there is an observation system in place to monitor the current information about the health status in each time period, **Ot**, that yields partial data about the true state. It is supposed that the observed information obtained by monitoring the system is a discrete variable. Therefore, it is assumed that the set of observation data can take on one of a possible set of values at time t:

$$\mathbf{Oi(t) = \{O1(t), O2(t), \ldots, Ok(t)\}} \tag{11}$$

The reliability of the obtained information about the current state of the population is critical. A reliability matrix, **R**, is used to capture the reliability of the observation as a conditional probability array. It is assumed that reliability matrix, **R**, corresponding to any control system is time invariant with constant variables. By knowing the current observation at time t, **Ot**, the impact on the probability distribution of the health status at time (t+1) can be updated via the efficient statistic of equation (8):

$$\mathbf{Pr\{Si(t+1)|Ot\}} = \frac{\mathbf{P\{Si(t)|Ot\} * Pt * P\{Ot|Si\}}}{\sum_{j=1}^{n} \mathbf{(P\{Sj(t)|Ot\} * Pt * P\{Ot|si\})}} \tag{12}$$

where $n=5$ is the number of discrete elements in the health status state space.

Pr{Ot|Si} is an element of the Reliability Matrix, where the probability of seeing the current observation is going to happen, given the health status Si of the population at time t.

Pr{Si(t)|Ot} is the updated probability of state Si at time t, given the information and history of the state obtained from the observation at time t, Ot.

Thus, by using the knowledge of the current state, the current observation, and the probabilistic transition, the probability of the next state can be obtained. A detailed example with a numerical illustration of this statistical model has been provided in the following chapter.

3.6 Gap Analysis

Consider all possible outcomes for the consumption of consumer products. There are three different Experiments:

(1) The population health is unaffected by the consumption of the product (benchmark)

(2) The population health indicates some improvement (product consumption is Positive)

(3) The population health indicates a downside affect (product consumption is Negative)

These scenarios can be considered to be formed based on observed outcomes and on collecting data, using health indicators, consumption rates, productions and some other data collections.

In the first two Experiments, there may be no incentive to intervene to adjust the health care status of the population. However in last Experiment, when the population health status shows some signs of negative impact attributed to the consumption of the product, there should be an intervention policy to stop or to slow down the deterioration in the health status process that is linked to the consumption of the product.

3.6.1 Benchmark Scenario

The first scenario is defined as the "benchmark", where the population health is assumed to be unaffected by consumption of the product. Suppose that observations for a twelve month period include seasonal differences and their normal effect on health status. In this scenario, since the general health is unaffected by the consumption of the product (beyond the expected seasonal shifts in health status), the system cycles through similar descriptions of the health care states.

The vector $P\{S(t)\}$ defines the health status of the population at time *t*. Time *t* is defined for a period of one year or twelve months, i.e., $t=1,2,\ldots 12$.

The following benchmark graph (Figure 3) demonstrates the population's health status in different seasons, and subsequently in different months. In this illustration, the chart is divided horizontally into five divisions or areas, representing "Excellent", "Good", "Acceptable", "Poor", and "Very Poor" health status of a particular population in a specific time t.

To show the boundary of each area in Figure 4, these divisions are differentiated by different colour segments, where the lower area of the chart represents the excellent condition (S1), while the upper area of the chart represents a very poor condition (S5). In case of the benchmark scenario, the seasonal effect on the health status of a population can be demonstrated. As time t is defined for a period of one year or twelve months, i.e., t =1,2,...12, the boundary of the very poor condition status has advanced vertically between (t = 5) and (t = 9). This is the period of time, between February to June, where more often a decline in health status of a population is disseminated due to several reasons including bad weather, and the higher probability of accidents, and reported illness.

A benchmark graph can be used as a reference to reveal the difference between boundaries of other possible scenario graphs and to examine the effectiveness of one health related policy over others. Figure 3 shows the benchmark graph.

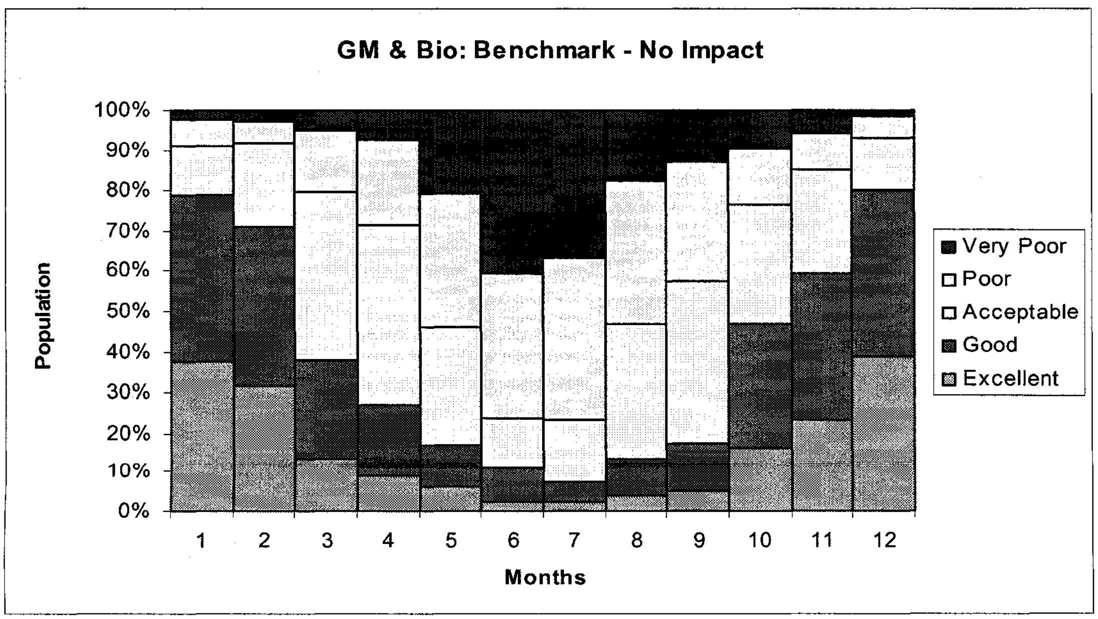


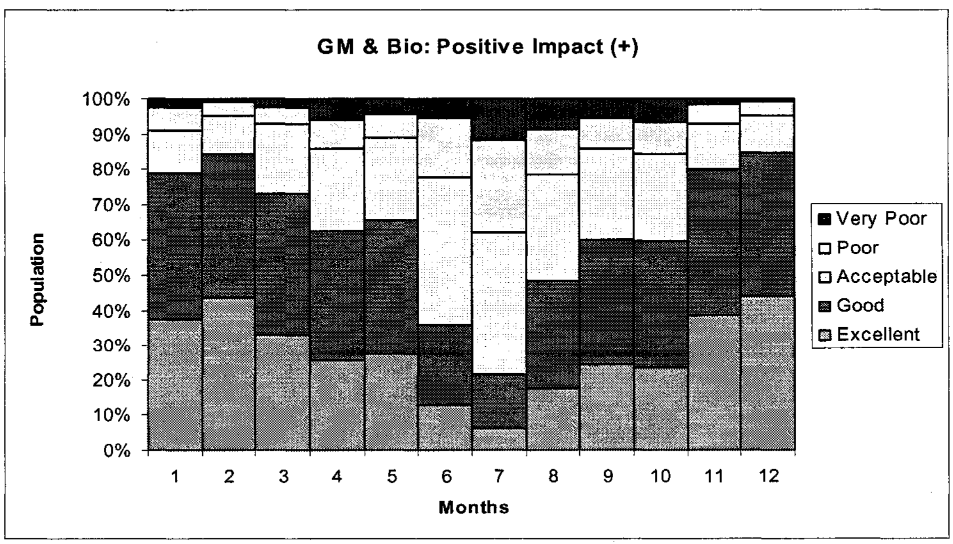
Figure 3: The result of a benchmark can be seen in a chart

The following sections demonstrate the two other Experiments of the improvement and the deterioration of a specific population at time t.

3.6.2 The Population Health Indicates Improvement

The second scenario illustrates an improvement in the health care description so that the consumption of the product appears to have a positive impact. By collecting the data and having a series of observations for twelve months in a year period, the seasonal differences along with an overall improvement of health status can be observed. In this scenario, because the general health indicates some improvement, a difference in the observation series can be seen. An illustration of this observation is demonstrated in a chart in Figure 4.

The previous benchmark graph (Figure 3), which is used as a reference to evaluate the other possible health scenarios, can be compared to the following positive graph, Figure 5. Through comparison and analysis of these two graphs (Figure 3 and 4), an obvious vertical retreat on the boundary of a very poor health status of the GM positive in Figure 5 can be observed, which is between periods February (t =5) to June (t =9). Also, there are some obvious advances on the boundaries of the excellent and the good health statuses, as shown in Figure 4. This is another sign of a population health status improvement due to an effective health policy.



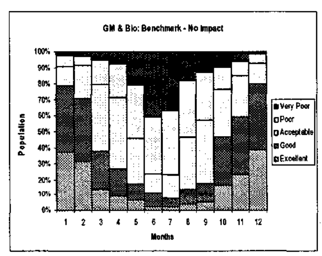


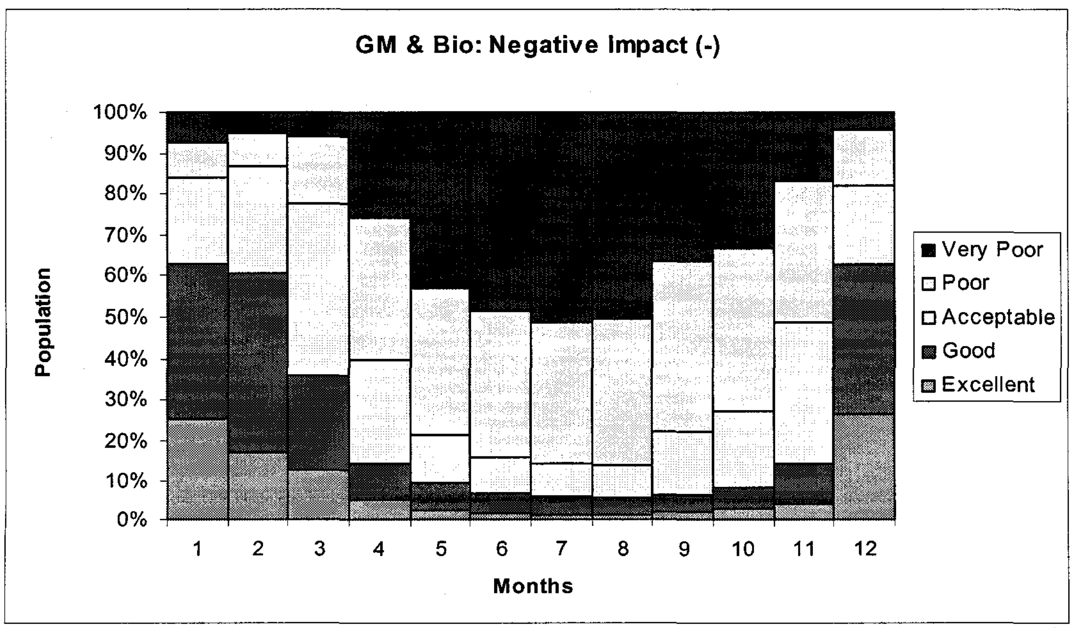
Figure 4: An example of the result of a Positive heath status can be seen in the above chart

By comparing the positive chart to the benchmark, an improvement of health status can be observed, where the area of the "excellent" health status is advanced and the area of the "very poor" health status is reduced.

3.6.3 The Population Health Indicates a Downside Affect

The third scenario illustrates a "negative" impact, whereby the population health description indicates a downside affect attributed to the consumption of the product. By collecting the data and having a series of observations for a twelve months period, the seasonal differences and the effect on the overall health status can be observed. In this scenario, the general health indicates a downside affect. These results are demonstrated in a chart in Figure 5.

The negative graph, Figure 6, illustrates the boundary changes contrasted to the benchmark graph. In comparison, an obvious vertical and horizontal advance in the boundary of a very poor health status occurs between February (t=5) to Jun (t=9). By contrast, the excellent and the good health statuses are reduced. There is a general decline in the health status of the population in the negative scenario.



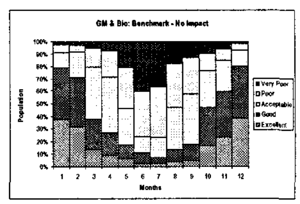


Figure 5: An example of the result of a Negative heath status can be seen in the above chart

In conclusion, by comparing the negative chart to the benchmark and the positive charts, we can see advancing of "Very Poor" status and the retreat of the "Excellent" and "Good" on health status. This comparison displays a gap between health conditions in different scenarios and suggests the need for a policy intervention.

3.7 Policy Adjustment

By observing these illustrated results, if the population health indicates a downside affect, a preventative policy should be adopted to arrest the health status decline. The system defines a "red line" or an "alarm" for decision makers so that they may apply proper action before it goes far deeper than the reduction of overall health status. To define the alarm, a health status value indicator is required. The range of this value can be defined by the many different parameters and factors, as discussed further below.

Define an alarm where, if the estimated probability value of the final state of S5 (very poor condition) exceeds 0.05 in any season, then, in the subsequent period, there will be the first type of intervention, denoted as "Low". If S5 exceeds 0.2 in any period, there will be a second type of intervention, which is denoted as "Moderate". If two successive S5 bars exceed 0.2, then there will be the third intervention, which is denoted as "Extensive".

Figure 6 illustrates how an alarm can be activated. In the following case example in a negative scenario, the "Very Poor" area is advanced and has passed the boundary of the 0.05 and 0.2 alarm injust a few months between February (t = 5) to August (t= 11). This triggers a need for an extensive intervention. Therefore, in each case, within its related simulation model, a possibility of an intervention based on a level of alarm is evaluated and if such an alarm is needed, the intervention and policy adjustment take place. The experimental model shows that a continuing intervention will help to reduce or maintain a potentially negative health impact.

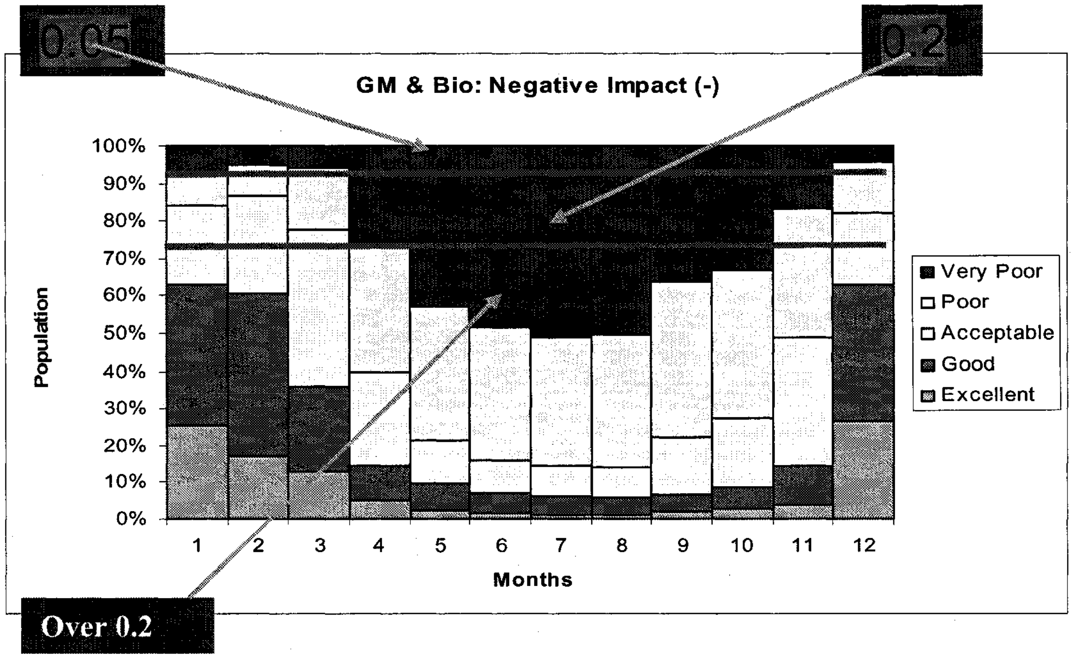


Figure 6: Demonstration of Alarm bars

Based on the above assumptions, we can arrange a role to implement a new policy to reverse the situation. In this thesis for illustration purposes, three different alarms are applied to examine their influence on health status.

3.8 Alarms

There are three types of alarms in this model: Low-alarm (Alarm 1), Moderate-alarm (Alarm 2) and Extensive-alarm (Alarm 3). Based on every type of alarm, a new set of period-over-period transaction matrices is defined. If the alarm is not in effect, the original state transition matrix is applied to generate the next transition. If the alarm is turned on, and it is a type (1), a new state transition is defined as a consequence of a health status intervention, where its states have modified and the overall health status transitions are approximately 10% improved versus the benchmark transitions. If the alarm is on and it is a type (2) the new state transaction is used, where its states are modified and the overall health status 25% is considered to be improved. If the alarm is on, and it is a type (3), then the new state transaction is used, where its states have modified and the overall health status, the new 40% is considered to be improved. This new state transitions will influence the next outcome state vector in a way that they will push the states to improve. The improvement is observed after continuing the intervention system for a few months.

3.8.1 Low-Alarm

In any month, during any season, if the very poor condition (S5) estimate exceeds the probability estimate of 0.05 but it is still less than 0.2, then the first alarm, Low-alarm, is in effect and the new health policy product consumption intervention is introduced such that the intervention causes an impact in the population state transition for the next month. For example, a new health policy product consumption intervention strategy may consist of producing labels on products advising against consumption for subgroups of the population, e.g., those with cholesterol or heart problems.

3.8.2 Moderate-Alarm

If in any month, during any season, the very poor condition (S5) estimate exceeds the probability estimate of 0.2, then a new alarm, Moderate-alarm, is in effect and the new policy is introduced such that the intervention causes an impact in the population state transition for the next month. A health policy product consumption intervention strategy of this type may be the restriction of product sales in a limited set of retail outlets, e.g., exclude supermarket distribution and sales, but permit sales in specialty nutrition and health stores and requiring new product labeling.

3.8.3 Extensive-Alarm

If in any month, during any season, the very poor condition (S5) estimate exceeds the probability estimate of 0.2 in two successive period consequently, or if the Moderate-alarm is on for two consequent months, then new alarm, the Extensive-alarm, is in effect and the new policy is introduced to state transitions such that the intervention causes an impact in the population state transition for the next month. For example, a health policy product consumption intervention strategy of this type may restrict sales of the product to prescription status requiring the permission of a doctor.

3.9 Intervention

The intervention is a function of the probability estimate of S5. Every alarm has a different intervention response, depending on the situation of the probability estimate for the very poor condition, S5 at the time. The interventions have two main characteristics: They correspond to the design of the post-market changes, and they have a specific length of intervention.

The extent of change is characterized by the type of intervention. Different interventions have been assigned for different situations. The three interventions and responses used in this model illustration are described as: Low, Moderate, and Extensive intervention. Each intervention is a reaction to a specific alarm type. The intervention has an impact between 10% low to as high as 40% on health status, as summarized in the table (Table 4) below.

Alarms Type:	**Interventions**	
	Extent	**Length**
Low	**Low (10% Change)**	**One Period**
Moderate	**Moderate (25% Change)**	**More Than One Period**
Extensive	**Extensive (40% Change)**	**Long Term**

Table 4: Table of different alarms and their related interventions

Chapter 3 described the model's methodology, model components, gap analysis and health state scenarios, and health state alarms triggering policy intervention strategies. Moreover, the methods such as the Bayes' theorem and the Markov Chain were described. The following chapter illustrates the model used in this research with a numerical example.

4. Models' Illustration

In this chapter, the partially observable model of post-market surveillance and policy intervention for the case of food product consumption and its implied health effects on a population is demonstrated. Presentation of the model is accompanied by a numeric example. Illustrative calculations to determine the next expected health status from partial observations or samples are shown under alternative intervention strategies aimed at improving the population's health status.

4.1 Models' Components

The following information is used to illustrate the model's example process for setting dynamic market policies given observations from surveillance of a product consumed in the marketplace. It is to be noted that in this illustration, data are set arbitrarily and do not imply actual cause and effect on population health from product consumption. The model contains the following components:

(1) States (5): Representing the distribution of health status of the population. These five health states are described as "Excellent", "Good", "Acceptable", "Poor", and "Very Poor" and designated as states S1, S2, S3, S4, and S5, respectively.

(2) Time: Each trial occurs over a 12 month planning period, starting from October 1st and ending on Sept 31st of each year.

(3) Seasonality: A year contains four seasons of three months each, Fall, Winter, Spring, and Summer. For every season there is a predefined seasonal state transition matrix that models the different changes in health status of the population in each season. Differences in seasonal transitions are expected to occur as a function of the season and are not solely due to the intervention strategy that may occur within each season.

(4) Trials: There are 10 independent trials of 12 months in length in each scenario of the original model.

(5) Alarms: There are three alarms that indicate the severity of the health intervention designated to take place in a given period. These are: Low-alarm (Alarm 1), Moderate-alarm (Alarm 2), and Extensive-alarm (Alarm 3). Each alarm is triggered by observations that affect a change in the probability estimate of the lowest health state, S5, or the "Very Poor" health status. There are interventions related to each level of alarm. These interventions are assumed to affect the subsequent health state transition matrix for the population, where an approximate change of 10%, 25%, and 40% applies to the state transition matrix, according to each severity of the alarm applied. (See Table 5 below)

Alarms' Type

Alarm's Type:	Alarm off: Type 0	Alarm on: Type 1	Alarm on: Type 2	Alarm on: Type 3
Conditions:	S5 <= 0.05	0.05 < S5 < 0.2	S5 >= 0.2	Alarm 2 has been repeated in last two time periods
Interventions:	No Intervention	10% Intervention	25% Intervention	40% Intervention

Table 5: Three types of alarms

The corresponding state transition matrices in response to the different type of alarms are shown in the following Tables 6-9. These tables represent the state transitions in the Fall season (October through December). The model has different state transitions in different seasons independent of the triggered alarms. The changes inn the seasonal transition matrices triggered by each alarm conditions affect the corresponding seasonal state transition matrix as described below.

In the case of No-alarm, the original, pre-specified seasonal transition matrix is used to move the population from its current health state into the next month. For instance, Table 6 demonstrates a single month population health state transition matrix within the Fall season, ie, between the months of October to December.

No-Alarm Transition Matrix-Fall

Period-Over-Period	From/To	S1 Excellent	S2 Good	S3 Acceptable	S4 Poor	S5 Very Poor	Total
S1	Excellent	0.45	0.3	0.15	0.075	0.025	1
S2	Good	0.2	0.45	0.2	0.1	0.05	1
S3	Acceptable	0.1	0.15	0.45	0.2	0.1	1
S4	Poor	0.05	0.05	0.15	0.45	0.3	1
S5	Very Poor	0.025	0.075	0.15	0.25	0.5	1

Table 6: The No-alarm period-over-period transition matrix in the Fall season.

When an alarm occurs during a season, the transition matrix is switched, as the consequence of the intervention in the population health, to a corresponding "alarmed" transition matrix. Depending on the level of the alarm, the original seasonal transition matrix will be modified accordingly. This modification is based on approximate percentage changes to the diagonal of the original transition matrix. As shown in Table 5, the Low-level alarm causes a 10% improvement (i.e., expected shifts into higher health states from lower health states) in the states of original transition matrix. For instance, the probability that a good health status is going to change to an excellent health status will improve from a 0.2 to a 0.22 percent, a 10 % improvement. However, since the total probability of all states in a row must remain 1, the 10% change is relative to the overall health status of the population. The following Table 7 shows a Low-alarm transition matrix in Fall that replaces Table 6 in the event of a Low-level alarm have been triggered from the previous period's S5 probability estimate, i.e, Pr(S5) exceeds 0.05. The health status transitions of Table 7 compared to the No-alarm Table 6 has improved (i.e., shifted into lower health states) by approximately 10%.

Low-Alarm (Type 1) Transition Matrix-Fall

Period-Over-Period	From/To	S1 Excellent	S2 Good	S3 Acceptable	S4 Poor	S5 Very Poor	Total
S1	Excellent	0.44	0.33	0.2	0.02	0.01	1
S2	Good	0.22	0.44	0.22	0.07	0.05	1
S3	Acceptable	0.11	0.22	0.44	0.15	0.08	1
S4	Poor	0.06	0.11	0.22	0.36	0.25	1
S5	Very Poor	0.03	0.1	0.16	0.35	0.36	1

Table 7: The Low-alarm (type 1) period-over-period transition matrix in the fall

The same strategy on the Low-alarm system applies to the effect of a Moderated-Alarm on a transition matrix, but with an approximate 25% improvement in the overall health status of a population. Table 8 shows a Moderate-alarm transition matrix in fall.

	Moderate-Alarm (Type 2) Transition Matrix-Fall						
Period-Over-Period		S1	S2	S3	S4	S5	
	From/To	Excellent	Good	Acceptable	Poor	Very Poor	Total
S1	Excellent	0.56	0.27	0.13	0.03	0.01	1
S2	Good	0.27	0.5	0.13	0.06	0.04	1
S3	Acceptable	0.15	0.3	0.29	0.16	0.1	1
S4	Poor	0.1	0.15	0.3	0.2	0.25	1
S5	Very Poor	0.08	0.1	0.15	0.25	0.42	1

Table 8: The Moderate-alarm (type 2) period-over-period transition matrix in the fall

An Extensive-alarm affects a transition matrix with an approximate 40% improvement is shown in the following Table 9.

	Extensive-Alarm (Type 3) Transition Matrix-Fall						
Period-Over-Period		S1	S2	S3	S4	S5	
	From/To	Excellent	Good	Acceptable	Poor	Very Poor	Total
S1	Excellent	0.65	0.25	0.06	0.03	0.01	1
S2	Good	0.35	0.51	0.1	0.01	0.03	1
S3	Acceptable	0.2	0.2	0.34	0.13	0.13	1
S4	Poor	0.15	0.18	0.2	0.22	0.25	1
S5	Very Poor	0.1	0.15	0.13	0.25	0.37	1

Table 9: The Extensive-alarm (type 3) period-over-period transition matrix in the fall

(6) Graphic Output: Model output consists of an annual graph for each trial, showing the monthly health status probability estimates distribution. There are 10 graphs for all trials in a given scenario, and one summary probability estimates distribution graph, which is the average of all the 10 independent trial graphs for the scenario.

(7) Cost Accumulation: Each trial has a related cost associated with the cost of its population health maintenance, and the cost of the triggered health interventions. The total cost of each annual trial is accumulated and the final cost of ten trials is stored in a table for cost analysis.

(8) Decision Trees: After storing the total cost for each scenario, all scenario costs are stored in a single table for comparison. Decision trees are used to determine the best health intervention option in each comparison trial.

4.2 The Seasonal Transition Matrices

Based on the change of each season, the health status of the population is expected to change, independent of the product consumption. This is modeled due to a greater possibility of colds and flu outbreaks and other seasonal illnesses in winter compared to summer, as well as spring and fall. Therefore, the state transition probability distribution matrices are adapted according to the season. Winter is considered as the worst case for transitions to deteriorating or poorer health status, and, summer, by contrast, the best season for improved transitions in health status. The interventions will occur within each state transition seasonal matrix. It is noted that data used in this illustration are set arbitrarily and do not imply cause and effect in product consumption to health status. The seasonal transition matrices (unaffected by intervention strategies, i.e., "no alarm") illustrated here are found in Tables 10 through 13 below.

Transition Matrix - Fall

State-to-State		S1	S2	S3	S4	S5
		Excellent	Good	Acceptable	Poor	Very Poor
S1	Excellent	0.45	0.3	0.15	0.075	0.025
S2	Good	0.2	0.45	0.2	0.1	0.05
S3	Acceptable	0.1	0.15	0.45	0.2	0.1
S4	Poor	0.05	0.05	0.15	0.45	0.3
S5	Very Poor	0.025	0.075	0.15	0.25	0.5

Table10: The period-over-period transition matrix for the Fall season (October through December)

Transition Matrix - Winter

State-to-State		S1	S2	S3	S4	S5
		Excellent	Good	Acceptable	Poor	Very Poor
S1	Excellent	0.2	0.3	0.3	0.15	0.05
S2	Good	0.15	0.2	0.15	0.2	0.3
S3	Acceptable	0.01	0.05	0.09	0.45	0.4
S4	Poor	0.02	0.02	0.06	0.4	0.5
S5	Very Poor	0.01	0.01	0.01	0.27	0.7

Table 11: The period-over-period transition matrix in the Winter season (January through March)

Transition Matrix - Spring

State-to-State		S1 Excellent	S2 Good	S3 Acceptable	S4 Poor	S5 Very Poor
S1	Excellent	0.27	0.22	0.15	0.16	0.2
S2	Good	0.2	0.2	0.2	0.15	0.25
S3	Acceptable	0.1	0.15	0.3	0.2	0.25
S4	Poor	0.05	0.05	0.15	0.4	0.35
S5	Very Poor	0.02	0.03	0.1	0.25	0.6

Table 12: The period-over-period transition matrix in the Spring season (April through June)

Transition Matrix - Summer

State-to-State		S1 Excellent	S2 Good	S3 Acceptable	S4 Poor	S5 Very Poor
S1	Excellent	0.6	0.35	0.03	0.01	0.01
S2	Good	0.5	0.4	0.06	0.02	0.02
S3	Acceptable	0.2	0.35	0.15	0.08	0.22
S4	Poor	0.1	0.25	0.15	0.2	0.3
S5	Very Poor	0.05	0.23	0.1	0.22	0.4

Table 13: The period-over-period transition matrix in the Summer season (July through September)

4.3 Observation Model

The model process assumes that the population is in an initial (unknown) health state in order to start generating the first observation series. Subsequent observations and states are determined based on initial state and these influence the following generation of series and observations. The following describes the model process. This first illustrative scenario assumed No-alarm and no interventions.

4.3.1 Initial State:

The actual initial health status is assumed for the entire population of interest. Let us assume that the initial state (t=0) of the population is in the state 1, S1, the excellent health condition. In vector notation, the perfect knowledge of the initial state can be expressed as a probability distribution vector across all 5 states, as follows: (1,0,0,0,0)

For estimation purposes, the population is divided into health status levels. The population is estimated to be distributed among percentages of healthy and non-healthy citizens. The population is grouped into the five different health statuses: “Excellent”, “Good”, “Acceptable”, “Poor”, and “Very Poor”. The excellent health condition (state 1) applies to very healthy group of people and the very poor condition (state 5) applies to the worst case health scenarios. Let the initial health state vector be as follows: (See Table 14):

	S1	S2	S3	S4	S5
Si(t) =	**0.2**	**0.4**	**0.2**	**0.15**	**0.05**

Table 14: The initial health state probability estimate

4.3.2 Initial Period-over-Period Transition

The probability of the health status in the next period is determined using the season specific transition matrix, Pt, which describes the probable transition of the states over one month. Assuming the period-over-period transition 5x5 matrix (Pt) as in Table 10 above (under no intervention):

The updated state probability for the monthly Fall transition can be calculated based on the above 5x5 matrix and the prior state probability distribution 1x5 vector by matrix multiplication.

Assume the actual initial health status (population in S1) and its vector distribution (1,0,0,0,0), pre-multiplying the Table 10 probability transition matrix by the prior state vector yields the probability that the health status in one month moves to alternative states over the Fall monthly period.

4.3.3 Next State

To simulate the model process, the next actual state can be determined randomly based on the Table 10 transition matrix by generating the state according to its probability of occurrence. This is done by randomly generating a number between 0 and 1, and is compared to the current state row representing the “From” state, S1 to S5. Since it is assumed that the first initial state was S1, the random generator value will be compared to the first row of the Table 10 matrix. For instance, if the random number generator provides a number, say 0.001, then the next simulated actual state will be S1; if the random number is in fact between 0 and 0.45, the next simulated actual state will be S1. If the random number is between 0.4501 to 0.75 (=0.45 + 0.3), the next simulated actual state will be S2, and so on. The same role applies for a random number between 0.75 and 0.9 (0.45 + 0.3 + 0.15) to determine S3. If the number exceeds 0.9, but is less than 0.975, then the simulated next state is S4. Finally if the number is greater than 0.975, then the simulated state will be S5.

4.3.4 First Observation (O1)

The health state of the population is under surveillance and yields observations about the health status of the population. Such observations are a function of the actual state of health of the population and the observation levels. Consider five different health observations and create a 5 by 5 state-to-observation matrix, or reliability matrix (also known as the maximum likelihood matrix in Bayes' analyses) as in Table 15 below:

Reliability Matrix

		O1	O2	O3	O4	O5	Total
S1	Excellent	0.4	0.3	0.15	0.1	0.05	1
S2	Good	0.3	0.3	0.2	0.1	0.1	1
S3	Acceptable	0.1	0.2	0.4	0.2	0.1	1
S4	Poor	0.07	0.1	0.28	0.3	0.25	1
S5	Very Poor	0.03	0.1	0.17	0.3	0.4	1

Table 15: The state of population under surveillance

where the cell (S1, O1) denotes the conditional probability of observing O1 given the actual state of the system is in S1, i.e., Pr(O1|S1)=0.4.

Suppose the actual state was simulated in month 1, t=1, is S3, the observation can be simulated from a randomly chosen draw from row three of Table 15, and if the random value for example is between 0.3 and 0.7 the observation value will be O4. This observation value will be used to calculate the updated health state estimate as a probability distribution for the subsequent period.

The new state vector can be determined based on the initial health state probability vector (Table 14), the seasonal transition matrix (Table 10), and the current observation value. First, the initial and period-over-period transition matrices are multiplied (Table 16):

Si(t) =

S1	S2	S3	S4	S5
0.2	0.4	0.2	0.15	0.05

{ Initial state vector }

X

From/To	S1	S2	S3	S4	S5
S1	0.45	0.3	0.15	0.075	0.025
S2	0.2	0.45	0.2	0.1	0.05
S3	0.1	0.15	0.45	0.2	0.1
S4	0.05	0.05	0.15	0.45	0.3
S5	0.025	0.075	0.15	0.25	0.5

{ State to State Transition Matrix }

Table 16: The product of initial and period-over-period transition matrices

The result will be:

Si'(t) =

S1	S2	S3	S4	S5
0.18875	0.27875	0.2575	0.1725	0.1025

{ Next state vector }

Table 17: The result of the product of initial and period-over-period transition matrices

Assuming the current period observation column was O4, then the new updated health state probability vector estimate over the states, Si'(2), will be found by multiplying the Table 17 results with the 4th column (O4) of the observation matrix, as follows:

Si'(t) =

S1	S2	S3	S4	S5
0.18875	0.27875	0.2575	0.1725	0.1025

{ Next state vector }

X

	O1	O2	O3	O4	O5
S1	0.4	0.3	0.15	**0.1**	0.05
S2	0.3	0.3	0.2	**0.1**	0.1
S3	0.1	0.2	0.4	**0.2**	0.1
S4	0.07	0.1	0.28	**0.3**	0.25
S5	0.03	0.1	0.17	**0.3**	0.4

{ Observation Matrix }

Table 18: The new state matrix Si'(2) and the 4th column of the observation matrix

This yields the result: 0.18075. By Bayes theorem (see equation 9 above), then every cell of the updated state vector will be divided by 0.18075 to yield the new state vector probability estimate:

	S1	S2	S3	S4	S5
Sj(t) =	0.104426	0.15421853	0.284924	0.28630705	**0.17012448**

Table 19: The new state probability state matrix Sj(t)

The worst Experiment, S5 and its probability is an important element of this vector that determines the health intervention to be applied in the next period. Since from Table 19 above, S5=0.17012 is greater than 0.05 and less than 0.2, the alarm is turned "On" and it invokes an alarm type "1", Low Alarm intervention.

Alarm type "1" invokes a change in the period-over-period transition matrix based on seasonality. Random generation of the next state will be randomly selected, assuming that alarm type (1) state transition matrix is applied as a consequence of the health intervention (see Table 7 above).

Using the Table 7 matrix and the random generator, the next actual state in month 2, t=2 may be generated as: S3.

Now using the Observation matrix (Table 15) and the new actual state, S3, the next observation state in month 2 may be generated, e.g., O5, the 5^{th} column of the observation matrix (Table 15).

Therefore, by following the same procedure using the last state vector elements, P{Sj(t)} and using the alarm type (1) state transition matrix relevant for the season, the next estimated state vector Pr{S(t)} vector will be determined:

	S1	S2	S3	S4	S5
Sj(t) =	0.07507157	0.20799646	0.190192	0.27464394	**0.25209574**

Table 20: The next estimated state vector P{S(t)} in period 3.

Since the S5 in Sj(t) is greater than 0.2, the new alarm for month 3 will be set to type (2), moderate alarm. Previously, the alarm in the previous period was type (1), low alarm. The final alarm will be calculated based on the new and value of these alarms in the last two months. The greatest value among these two alarms will be passed into the final alarm value. If both alarms are equal to type

(1), the final alarm will be set to type (1); however, if both alarms are equal to type (2) twice in a row, it will trigger the extensive type alarm (3). The Extensive-alarm (3) will be used if the Moderate-alarm type (2) is repeated twice. In the case of repetition of the alarm type (3) in two consequent months, the final alarm will be type (3), or Extensive-alarm.

Therefore the final alarm in this example, based on the last two months, t=1 and 2 (or October and November) will be type (2), or a Moderate alarm intervention in t=3, December.

The same procedure will be applied to the next months of December through September, using new alarms status and the new state transition matrices, as required.

In this chapter, the partially observable model of post-market surveillance and policy intervention for consumption of products was demonstrated using a numeric example over the initial transitions of the surveillance process. The following chapter applies the model process to an application of food consumption, using obesity as the descriptor of the health state. Obesity has been considered a serious health issue. Health surveillance of obesity is motivated by the consumption of complex carbohydrates and modified foods.

5. Case Study

This chapter presents a complete example of the proposed post-market surveillance model as described in the previous chapter. The example studies a case in which post-market surveillance is used to access evidence for the advantages and disadvantages of consumption on the health status of a population. The case postulates how unhealthy products might impact specific aspects of the health status of the population and how policy interventions related to product consumption can be made to respond to negative health observations. The health status focuses on the important issue of population obesity and assumes, for the sake of illustrating the model procedures that the consumption of complex food products as a whole contributes to the worsening obesity condition. To this end, reported statistics about the seriousness of obesity and the linkages of consumption and the evidence of obesity are discussed below.

The obesity problem in our population is only partially observable, given the effective lack of surveillance systems in place and absence of reliable prevention policies. The following sections discuss the application of the post-market surveillance model to population consumption of complex food products and the assumed link to the obesity health issue by attributing surveillance and control to policy interventions.

It should be noted that links from population consumption to obesity are assumed in order to demonstrate model procedures. It is not the purpose of this thesis to confirm or deny specific links from consumption to obesity. Rather the purpose is to assume a probabilistic, dynamic structure to describe the real case including illustrative, intuitive data structures. Further, the understanding of this partially observable model helps to shape research in the area of complex population health interactions, currently underway for the topical problem of obesity. As such, research directed at defining model data structures provides the drivers for the analysis of actual consumption-obesity linkages toward the ultimate use of the information in health policy analysis.

5.1 Population Obesity

Obesity is a serious problem facing Canadians, both adults and children. During the past 25 years, obesity rates have increased substantially in Canada and the U.S.A. (Statistics Canada, 2005a). These countries are experiencing an epidemic of obesity and are confronted with increasing rates of related complications. Heart disease, diabetes mellitus, elevated lipid levels, and hypertension are only some of the most common related problems related to obesity. Much research is being done to find the main source and causes of obesity. Apart from the impact of new technology on life styles, and the absence of proper exercise, most scientists agree that food and diet play critical roles in obesity (Statistics Canada, 2005a).

Statistics Canada (2004) data show that the obesity rates among children and adults have increased substantially during the past 25 years.

> "In 1978/79, 3% of children aged 2 to 17 were obese. By 2004, 8%, or an estimated 500,000 children, were obese. Among adults, the growth in obesity was even more dramatic. In 1978/79, the age-adjusted adult obesity rate was 14%. A quarter century later, 5.5 million individuals, representing 23% of adults, were obese. Among young people, the biggest increases in obesity rates over the past 25 years occurred among adolescents ages 12 to 17, where the rate tripled from 3% to 9%. For adults, the most striking upturns occurred among people who were aged 25 to 34, and those who were 75 or older where the rates more than doubled to 21% and 24% respectively." (Statistics Canada, 2005a)

The Statistics Canada report, in 2004, illustrates the comparative obesity rates by age group in Canada for 1978/79 versus 2004 based on 2005 statistics (Statistics Canada 2005a). The evidence shows that in all age groups there is a more than doubling of the obesity rate in Canada. The report shows an increase in percentage of the obesity rate from 3% for the age group of 12-17 years old in 1978/79 to 9% in 2004. Similarly, obesity rate in the age group of 25 to 34 years old is being more than doubled from 9% to 21%., in age group of 75+, similarly it has increased from 11% to 24 % (Statistics Canada 2005a).

Similarly, research done by the Government of Alberta (2004) indicates the substantial overweight and obesity rates among adults 20-64 years old in Canada in 2000-2001, based on sex and age orientations, provincial locations, educations and income (Figure 7).

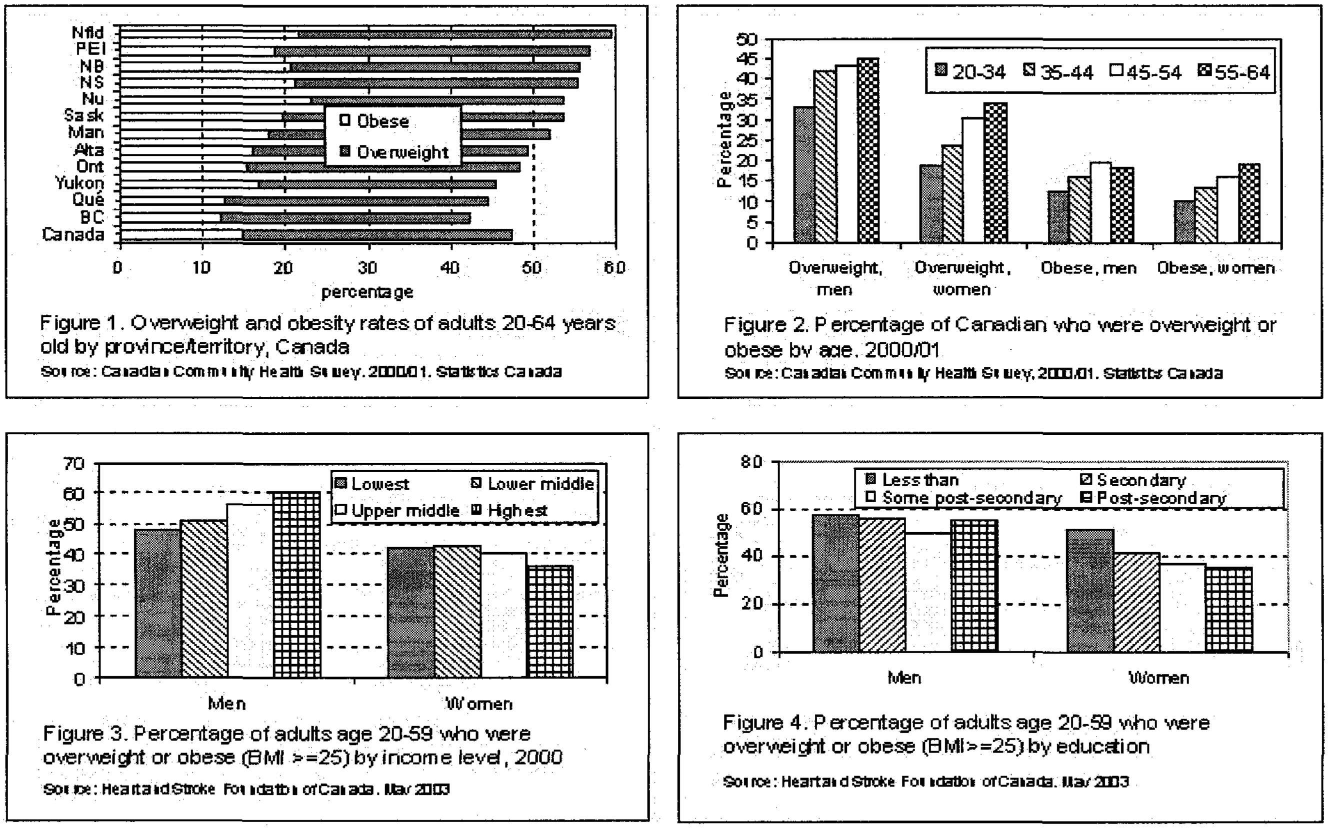


Figure 7: Obesity rate in different age and race (Government of Alberta, 2004)

Obesity has been described by some researchers as an epidemic disease. This was concluded based on the rate of change in the obese population and its magnitude, for example, as Starky (2005) states:

> "In 2004, approximately 6.8 million Canadian adults ages 20 to 64 were overweight, and an additional 4.5 million were obese. Roughly speaking, an adult male is considered overweight when his body weight exceeds the maximum desirable weight for his height, and obese when his body weight is 20% or more over this desirable weight. A similar guideline holds true for women, but at a threshold of 25% rather than 20%. Dramatic increases in overweight and obesity

among Canadians over the past 30 years have been deemed to constitute an epidemic." (Starky, 2005)

The following table (Table 21), from the Starky's research indicates a rapid increase in the overweight and obese population in Canada from 2001 to 2004.

	Overweight, Including Obese			**Obese**		
Year	**2000-2001**	**2003**	**2004**	**2000-2001**	**2003**	**2004**
Total	47.4	48.5	58.8	14.9	15.4	23.4
Men	55.6	58.1	65.2	16	16.6	23.7
Women	39	38.6	52.4	13.8	14.1	23.2

Table 21: The prevalence of the overweight and obesity among Canadian adults (%) (Statistics Canada, 2005)

The following section describes indications that media has influenced food consumption that have been attributed to the noted rise in obesity.

5.1.1 Media and Food Consumption

The media has encouraged the public consumption of foods that are high in fat. According to the November 21st's 2006 edition of the Ottawa Citizen, a study had found that 78% of the food advertisements during adult programming campaigns were for foods high in either fat, sodium, cholesterol or sugar (Kirkey 2006). The same report mentions that

> "Annual sales of food and beverages to children and youths were more than $27 billion U.S. in 2002 alone, and marketers are targeting children more aggressively, more brazenly and more directly. Harvard researchers reported in April 2006 that children consume an extra 167 calories for each additional hour of television watching about the same amount of calories in a can of pop. The team concluded that children eat what they watch." (Kirkey 2006)

The food industry does not agree with the report and they believe the blame is on children themselves. "The industry argues they have become a punching bag for the obesity crisis and that the problem isn't food advertising, but that children today are less active." (Kirkey 2006)

There is no question that obesity is becoming an increasing problem and this problem is growing. There are health risks associated with obesity. As the obese population grows, the health risks go up. The following section describes the health risks associated with obesity.

5.1.2 Obesity and Associated Health Risks

Health risks associated with obesity are increasing. This is evident in the declared economic impact of obesity: "It is estimated that direct costs of medical treatments attributed to obesity were $1.8 billion in Canada in 1997 and US$75 billion in the U.S.A. each year." (Birmingham, 1999; Finkelstein, 2004).

Statistics Canada reported that Canadians who are obese or overweight are more likely to have certain diseases (Statistics Canada, 1999). Table 22 below demonstrates the elevated impact of obesity compared to the "normal weight" population for related serious diseases.

Cases:	Overweight	Obese
Diabetes	1.73	3.97
High blood pressure	1.86	3.26
Arthritis	1.30	2.01
Thyroid disorders	1.39	1.75
Asthma	1.21	1.59
Heart disease	1.08	1.59
Back problems	1.13	1.36

Table 22: Table of selected health characteristics ratios to compare overweight and obese with normal weight population between aged 20 to 64 years, from source, Statistics Canada (Government of Alberta, 2004)

These health risks resulting of obesity are in turn linked to the leading causes of death in Canada. These leading causes of death include diabetes, cancer, and respiratory diseases. The following section applies the partially observable to the case of consumption and obesity.

5.2 Surveillance Model for Obesity

The partially observable surveillance model is described to observe obesity in a population whose health status is assumed to be adjusted by adjusting levels of consumption of obesity inducing foods. Presentation of the model will be made with a numeric example.

5.2.1 Obesity Model Components

The following method is used to illustrate the model example process for setting dynamic policies given observations from surveillance of obesity in a defined population. The model contains the components as follows:

(1) States:

Let the vector S(t) denote the obesity status of a consuming population at time *t*.

Let Si, i =1,2,3,4,5, denote each element of the vector, to indicate one of set of discrete "obesity outcome" states attributed to the population of interest. The obesity state of the population at time t is initially described by a prior probability distribution on the states of obesity from, as follows:

Let Pr{Si (t)} = Probability that the population is in obesity state i, i=1,2,3,4,5

where S1 denotes "Fit & Healthy", S2 denotes "Average", S3 denotes "Heavy" S4 denotes "Overweight", and S5 denotes "Obese".

(2) Time: each trial occurs over a period of 12 months, starting from October 1st to September 31st.

(3) Seasonality: A year contains four seasons of duration 3 month each, and for every season there is a specific state transition matrix since the health status of the population in each season differs.

(4) Trials: there are 10 trials of 12 months each for an experiment of the original model.

(5) Experiments: there are 4 separate experiments carried out on the original model corresponding to the selection of possible health intervention strategies.

(6) Alarms: There are four alarms denoted as No-alarm (Alarm 0), Low-alarm (Alarm 1), Moderate-alarm (Alarm 2), Extensive-alarm (Alarm 3), where each apply to a level of change in the estimate of S5, obese health status.

(7) Interventions: there are specific interventions related to each alarm. They influence the relevant seasonal state transition matrix, where a change of 0% (No-policy intervention), 10% (Low-policy intervention), 25% (Moderate-policy intervention), and 40% (Extensive-policy intervention) applies to the state transition matrix, corresponding to No-alarm (Alarm 0), Low-alarm (Alarm 1), Moderate-alarm (Alarm 2), or Extensive-alarm (Alarm 3) respectively.

(8) Graphical Output: for each trial, a summary graphic shows the monthly health status probability distribution estimates for the population. There are 10 graphs for each trial and one final summary graph, which is the average of all 10 trial graphs for the experiment.

(9) Cost: The total costs of alarms and health status are calculated for a cost decision analysis.

5.2.2 Obesity Model Experiments

The obesity model is applied in four different experiments, corresponding to No-alarm (Alarm 0), Low-alarms (Alarm 1), Moderate-alarms (Alarm 2) or Extensive-alarms (Alarm 3) and their associated Low, Moderate, and Extensive health intervention strategies.

For simplicity, the four alarms used in this model are as a function of the single estimate of the Pr{S5(t)}, obese health status, as described in Table 4 (Section 4.1). Each alarm has its own condition to trigger its intervention for improvement of the system. The conditions and intervention levels are shown as in Table 5 (section 4.1). Interventions denote the change in the seasonal transition probability matrices. The four intervention experiments refer to the progressively more intrusive health intervention strategy designed to improve the population health's status. The first experiment uses no intervention (No Alarm), whereas the fourth experiment includes the option to intervene with the Extensive Alarm, the most intrusive health option. The results of the alternative health intervention experiments are described, including their respective estimated costs of intervention, as noted below.

5.2.3 State Seasonality Transition Matrices

Based on the nature of each season, the propensity for obesity is expected to change. This is because, for example, there is a greater possibility of gaining weight because of being inactive in winter compared to summer as well as spring and fall. Therefore, the state transition probability matrix is unique to that season. Winter is considered as the worst season for obesity cases and summer, by contrast, the best health status season.

Four single period (monthly) period-over-period probability transition matrices are used to simulate the effect of each season's monthly changes on the health status states of a population. There are four seasons in the year (Fall, Winter, Spring, and Summer) each with three months duration. All probability transition matrices are stochastic matrices, i.e., their rows sum to one, and each cell {ij} of the matrices represent the probability that state i moves to state j in the course of one month. The Tables 10-13 (in section 4.2), are used (with the appropriate obesity health states: S1 denotes "Fit & Healthy", S2 denotes "Average", S3 denotes "Heavy" S4 denotes "Overweight", and S5 denotes "Obese") and showing the seasonality transition matrices used in this obesity surveillance case study. As before, all data have been estimated by the author and are attributed to logical constructs developed to illustrate the model.

5.2.4 Transition Response Matrices

The probability transition matrix is a key element that responds to an alarm type. When an alarm has been triggered, the corresponding transition matrix responds by marking the effect of the intervention on the transition of the population with respect to health status. Therefore, for each type alarm there is a specific probability transition matrix. These transition matrices are subject to change according to season. As a result, each season has its own transition matrix which changes through its alarm response. For instance, if the Low-alarm (Alarm 1) is on, the original transition matrix will switch to a low level (10%) transition matrix compared to the current transition matrix. In the case of a Moderate-alarm (Alarm 2), the original transition matrix will switch to a moderate level (25%) transition matrix, and in the case of the Extensive-alarm (Alarm 3), the original transition matrix will switch to a high level, or, 40% of the transition matrix. The 10%, 25% or 40% represents the approximate percentage of change of the original probability transition matrix in the corresponding season of the intervention. (See also Appendix 2 for more details)

(1) No-Alarm Transition Matrices

Tables 10-13 show the seasonal probability transition matrix example for the No-alarm case matrix with the redefined state definitions for S1 through S5.

(2) Low-Alarm Transition Matrix

The same example above of the Fall season is used to demonstrate a Low-alarm probability matrix with an approximate 10% change to Table 6 to improve the transition of the health status in response to the low level policy intervention. Table 7 provides the Low-alarm probability matrix for the Fall with the redefined state definitions for S1 through S5.

(3) Moderated-Alarm Transition Matrix

The same example of the fall season is used to demonstrate a Moderate-alarm probability matrix with approximate 25% changes to Table 6 to improve the transition of the health status in response to the moderate policy intervention. Table 8 provides the Moderate-alarm probability matrix for the Fall with the redefined state definitions for S1 through S5.

(4) Extensive-Alarm Transition Matrix

Finally, the same example of the fall season is used to demonstrate an Extensive-alarm probability matrix with an approximate 40% change to Table 6 to improve the transition of the health status in response to the extensive policy intervention. Table 9 provides the Extensive-alarm probability matrix for the Fall with the redefined state definitions for S1 through S5.

5.2.5 Reliability Matrix

The reliability matrix provides probability distributions for describing the observations about health status that may occur, assuming that the population is actually in a particular health status. The reliability matrix, R, represents the reliability of the state-to-observation probabilities as in Table 3 for the obesity case study with the redefined state definitions for S1 through S5.

In this obesity case study, observation about the health status is the act of observing and recording obesity related measurements for a given population. The scale of this measurement is from a very healthy condition of the "Fit & Healthy" (S1) to a very unhealthy condition of the "Obese" (S5), based on the weight of individuals in a given population.

Given a true statement of the actual health status, the rows of the obesity reliability matrix represent the probability distribution across the discrete observation possibilities, e.g., assuming that the population is actually in a "Overweight" state (S3), then there is a 7% probability that Observation #1, O1, will occur as the observation from the population sample.

Assume that information about the actual obesity status of the population can be observed from a surveillance system in each time period. Sample observations cannot reveal the actual obesity status of the whole population, but yields only partial information about the true state of the obesity status of the overall population. Actual obesity related data can be collected through hospitals, pharmacies, clinical and family doctors' reports.

5.3 Model Experiments

In the previous section, the obesity model, its states, and the transition and observation matrices were defined. This section will demonstrate the experimental obesity model and results.

5.3.1 The Alarms, Interventions and Experiments

The alarm options and related intervention strategies, which is triggered by S5 (the obesity state), are used to define model experiments. Each experiment used varying health interventions triggered by the S5 alarms. The four experiments, as described in Table 4 represent the different alarm options and associated intervention strategies:

- Experiment I: No-alarm model; No intervention
- Experiment II: Low-alarm model; Low intervention levels
- Experiment III: Moderate-alarm model; Moderate intervention levels
- Experiment IV: Extensive-alarm model; Extensive intervention levels

In Experiment I, No-alarm model, no alarm will be triggered. Therefore the monthly health transitions observations, and updated obesity status probability estimates are being determined but without any policy implementation, and without any external influences such as alarms.

In Experiment II, Low-alarm model, the interval range of an alarm associated with a low of 0.1 and a high of 0.3, which are 10% and 30% obesity rate for the S5 estimate. For instance, if the obesity state, S5, is greater than or equal to 0.3, the low alarm triggers a Low intervention (10% adjustment) applied to the relevant seasonal transition matrix. If the S5 estimate falls between 0.1 and 0.3, this triggers a Moderate intervention (25% adjustment) applied to the relevant seasonal transition matrix. If the S5 is less than or equal to 0.1, no alarm or intervention will be triggered. The final low-alarm is based on an old and a new alarm, and in each Experiment it is calculated differently as shown in Table 23 below for the Experiment II, Low-alarm model:

Experiment II: Low-alarm model

Alarm's Type:	Alarm on: Type 0	Alarm on: Type 1	Alarm on: Type 2	Alarm on: Type 3
Conditions:	S5 <= 0.1	0.1 < S5 < 0.3	S5 >= 0.3	Alarm 2 has been repeated in last two time periods
Interventions:	No Intervention	10% Intervention	25% Intervention	40% Intervention
Final Alarm:	IF (New Alarm >= Old Alarm) then: Final Alarm= New Alarm **Else:** Final Alarm= 0			

Table 23: Alarms in Experiment II: Low-alarm model

In Experiment III, Moderate-alarm, the interval range of an alarm associated with a low of 0.05 and a high 0.2 (instead of 0.1 and 0.3 in the Experiment II) which are the 5% and 20% obesity state probability estimate (S5) in the population. For instance, if the obesity state, S5, estimate is greater than or equal to 0.2, the alarm triggers a Type 2, Moderate intervention. If the S5 estimate is between 0.05 and 0.2, the alarm is low which triggers a Low or Type 1 intervention; otherwise, if the S5 estimate is less than or equal to 0.05, no alarm will be triggered. The Experiment III, Moderate-alarm and intervention model is summarized in Table 24 below.

Experiment III: Moderate-alarm

Alarm's Type:	Alarm off: Type 0	Alarm on: Type 1	Alarm on: Type 2	Alarm on: Type 3
Conditions:	S5 <= 0.05	0.05 < S5 < 0.2	S5 >= 0.2	Alarm 2 has been repeated in last two time periods
Interventions:	No Intervention	10% Intervention	25% Intervention	40% Intervention
Final Alarm:	**If** (New Alarm >= Old Alarm), **Then:** Final Alarm = New Alarm, **Else:** Final Alarm = 0			

Table 24: Alarms in Experiment III: Moderate-alarm model

In Experiment IV, Extensive-alarm, the interval range of an alarm, similar to Experiment III, and is associated with a low of 0.05 and a high of 0.2 probabilities of obesity rates (S5) in the specified population. Although the interval range of alarms in Experiment IV is the same as Experiment III, its final alarm is different. See Table 25 for Experiment IV, Extensive-alarm model details.

Experiment IV: Extensive-alarm

Alarm's Type:	Alarm off: Type 0	Alarm on: Type 1	Alarm on: Type 2	Alarm on: Type 3
Conditions:	S5 <= 0.05	0.05 < S5 < 0.2	S5 >= 0.2	Alarm 2 has been repeated in last two time periods
Interventions:	No Intervention	10% Intervention	25% Intervention	40% Intervention
Final Alarm:	**If:** (New Alarm > Old Alarm), Then: Final Alarm = New Alarm, **Else If:** {(New Alarm = Old Alarm) AND ((New Alarm Type = 2) OR (New AlarmType = 3))} Then Final Alarm Type = 3, **Else:**Final Alarm = Olds Alarm			

Table 25: Alarms in Experiment IV: Extensive-alarm model

5.4 Experimental Analysis and Results

In this section numerical results are presented for the different experiments defined above.

5.4.1 Experiment I: No-Alarm Model

As was described in the last section, the updated state is calculated at the end of each month. By repeating the same process for the consecutive twelve months, a final table for the health status of all twelve months in a one year trial period is found. Table 26 below demonstrates the twelve months health status for the obesity model without any alarm for one trial.

Experiment I. No-alarm scenario

States

		Fit & healthy	Average	Heavy	Overweight	Obese		
		S1	**S2**	**S3**	**S4**	**S5**		
Months	**Oct**	0.38	0.42	0.13	0.06	0.02	**1**	Periods
	Nov	0.32	0.40	0.21	0.05	0.03	**2**	
	Dec	0.42	0.41	0.12	0.04	0.01	**3**	
	Jan	0.08	0.09	0.21	0.36	0.25	**4**	
	Feb	0.09	0.11	0.13	0.29	0.38	**5**	
	Mar	0.01	0.01	0.02	0.30	0.66	**6**	
	Apr	0.01	0.02	0.09	0.36	0.52	**7**	
	May	0.10	0.12	0.19	0.24	0.35	**8**	
	Jun	0.18	0.19	0.19	0.19	0.26	**9**	
	Jul	0.59	0.35	0.03	0.02	0.01	**10**	
	Aug	0.57	0.38	0.03	0.01	0.01	**11**	
	Sep	0.57	0.38	0.03	0.01	0.01	**12**	

Table 26: The table of twelve months health status for the Experiment I: No-alarm scenario.

Figure 8 below shows the representation graph for this single Experiment I trial.

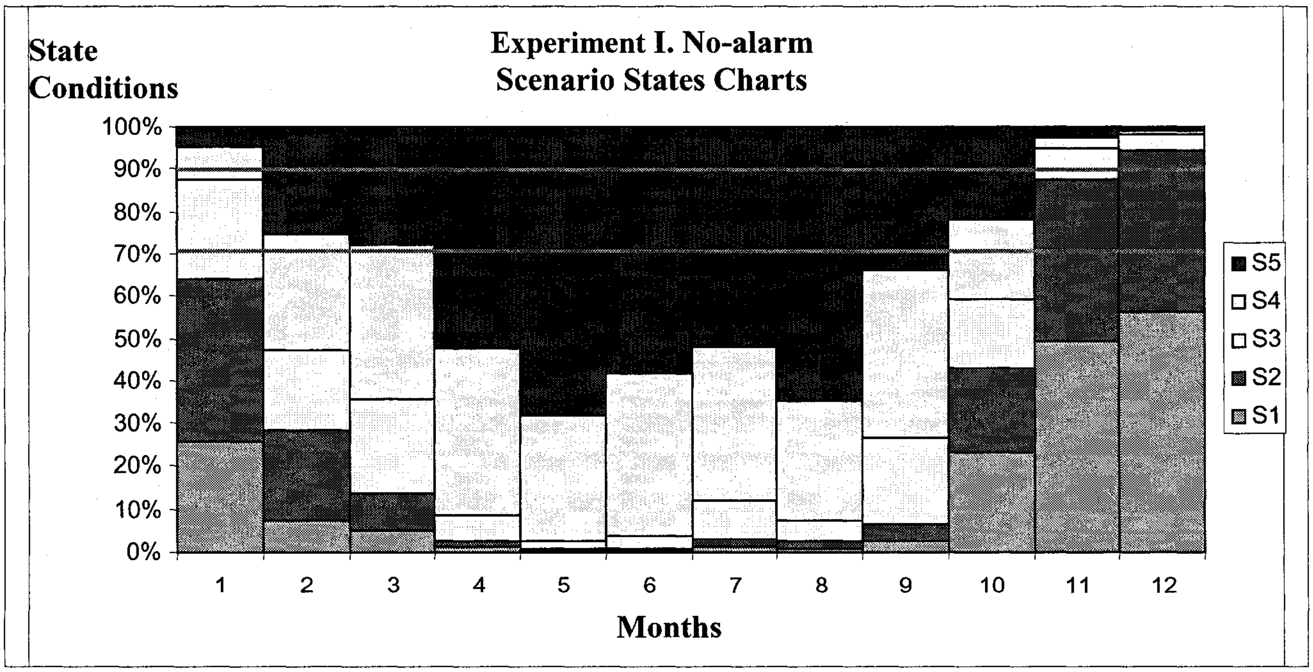


Figure 8: The graph for a single trial of the Experiment I: No-alarm scenario.

Figure 9 for Experiment I: No-alarm scenario reveals that the obese (S5) state has covered a vast area of the graph. It has approximately covered more than 60% of total graph area, and has advanced more in some specific periods, specifically between the months of January to June. Also, as it is displayed in this graph, January, February, and March are the worst case obesity-related months, where the S5 has passed both alarm trigger lines of Type 1 (low alarm) and Type 2 (moderate alarm) even though both alarms are "off" in this model, i.e., they do not trigger a health intervention. This graph can demonstrate a case without an intervention policy and any alarm system, in which higher levels of obesity is being spread throughout the population.

The same procedure described above is repeated for ten independent trials. All the ten corresponding trials are collected and their following graphs are found in Appendix 2 (Experiment I: No Alarm Trials).

Generally the ten different trials show similar results, even though the S5 distribution in each trial is different from one another. The overall average shows that the S5 has bigger area in the winter season in comparison with other seasons. The averages of all the ten final health status trials are found in Table 27.

Average of 10 Trials for the Experiment I. No-alarm Scenario

		States						
		Fit & healthy	**Average**	**Heavy**	**Overweight**	**Obese**		
		S1	**S2**	**S3**	**S4**	**S5**		
Months	**Oct**	0.16	0.25	0.29	0.19	0.11	**1**	Periods
	Nov	0.15	0.23	0.27	0.20	0.14	**2**	
	Dec	0.14	0.21	0.24	0.23	0.18	**3**	
	Jan	0.03	0.04	0.11	0.37	0.46	**4**	
	Feb	0.05	0.05	0.06	0.36	0.47	**5**	
	Mar	0.01	0.01	0.05	0.37	0.56	**6**	
	Apr	0.04	0.05	0.14	0.34	0.43	**7**	
	May	0.11	0.10	0.11	0.28	0.39	**8**	
	Jun	0.10	0.11	0.16	0.26	0.36	**9**	
	Jul	0.30	0.32	0.11	0.11	0.16	**10**	
	Aug	0.39	0.35	0.09	0.07	0.10	**11**	
	Sep	0.52	0.36	0.07	0.03	0.02	**12**	

Table 27: The summary table of ten health status trials for Experiment I: No-alarm

Similarly, the final average chart, Figure 9, represents the results of all the ten trials' monthly health status estimates for Experiment I: No-alarm. The average of all ten trials has similar results compared to the first trial that was previously described. The winter and spring seasons account for the obesity distribution in the graph, and overall, the state of obesity has advanced over 60% of the population.

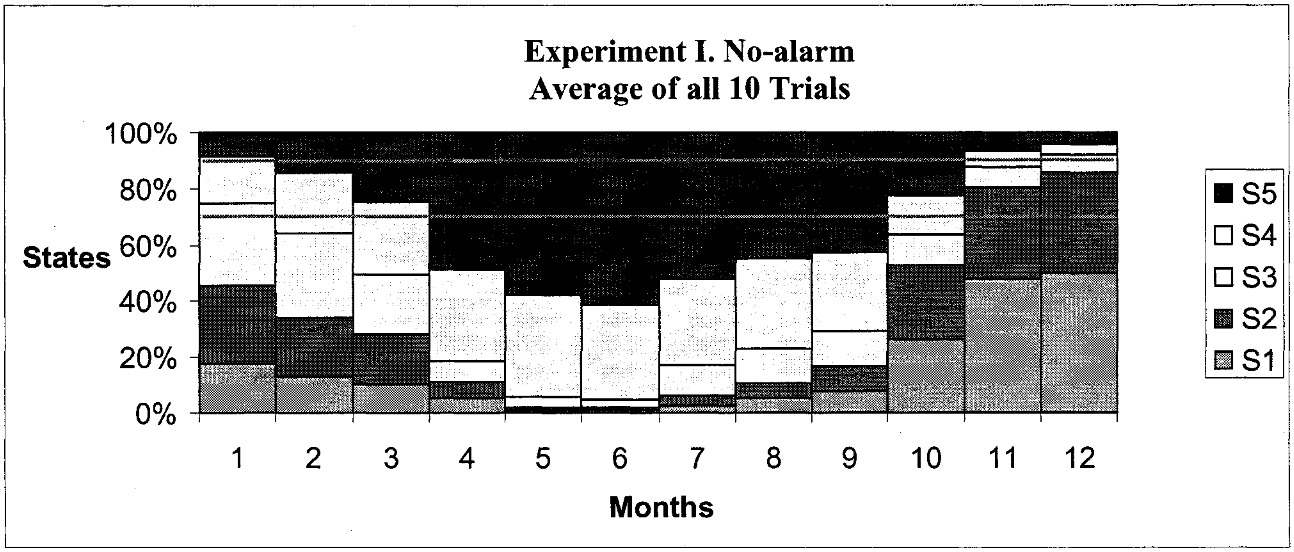


Figure 9: The average of all ten trials graph for Experiment I: No-alarm scenario.

5.4.2 Experiment II: Low-Alarm Model

The same procedure for Experiment I: No alarm is followed for Experiment II, Low-alarm scenario. The following table (Table 28) demonstrates the results for a single trial of the twelve months health status for the Experiment II, Low-alarm:

Experiment II. Low-alarm

		States						
		Fit & healthy	Average	Heavy	Overweight	Obese		
		S1	S2	S3	S4	S5		
Months	Oct	0.10	0.15	0.28	0.29	0.17	1	Periods
	Nov	0.07	0.11	0.28	0.28	0.26	2	
	Dec	0.05	0.09	0.25	0.34	0.27	3	
	Jan	0.01	0.02	0.03	0.30	0.65	4	
	Feb	0.00	0.01	0.02	0.27	0.70	5	
	Mar	0.05	0.05	0.10	0.31	0.50	6	
	Apr	0.05	0.08	0.27	0.35	0.26	7	
	May	0.03	0.04	0.12	0.34	0.47	8	
	Jun	0.03	0.04	0.13	0.36	0.45	9	
	Jul	0.16	0.24	0.05	0.17	0.39	10	
	Aug	0.21	0.26	0.04	0.14	0.35	11	
	Sep	0.67	0.29	0.02	0.01	0.01	12	

Table 28: The table of twelve months health status for Experiment II: Low-alarm scenario.

The results (for the single independent trial of Table 28) are demonstrated in the following graph (Figure 10):

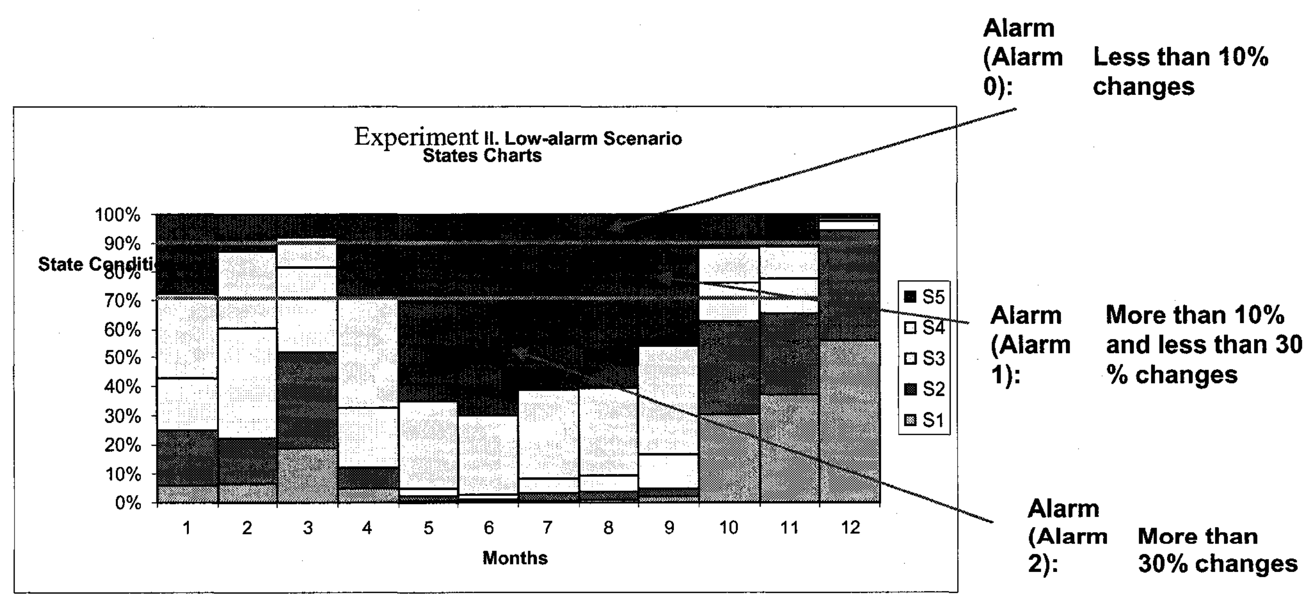


Figure 10: The graph for Experiment I: Low-alarm scenario.

The above graph for Experiment II, Low-alarm scenario is compared with the previous case of No-Alarm scenario. In comparison, the obese (S5) state has covered a larger portion of the population; however there are some improvements in some periods in winter and spring seasons, specifically between the months of January and June. The S5 estimates have still triggered alarms Type 1 (low) and Type 2 (moderate) in both experiments.

By repeating the exercise for ten randomly generated actual state transitions and observation monthly trials, the corresponding graphs are found in Appendix 2 (Experiment II: Low Alarm Trials).

By taking the average of all ten trials, we illustrate the results in one single table, and obtain the following average table (Table 29) for the Experiment II, Low-alarm:

Experiment II: Low-alarm (Average)

		States					
		Fit & healthy	**Average**	**Heavy**	**Overweight**	**Obese**	
Months		**S1**	**S2**	**S3**	**S4**	**S5**	Periods
	Oct	0.24	0.33	0.22	0.13	0.08	**1**
	Nov	0.22	0.29	0.28	0.14	0.07	**2**
	Dec	0.31	0.36	0.20	0.08	0.04	**3**
	Jan	0.13	0.11	0.09	0.28	0.39	**4**
	Feb	0.07	0.05	0.05	0.31	0.52	**5**
	Mar	0.02	0.02	0.07	0.35	0.53	**6**
	Apr	0.11	0.12	0.21	0.30	0.26	**7**
	May	0.12	0.11	0.14	0.27	0.36	**8**
	Jun	0.12	0.12	0.13	0.27	0.36	**9**
	Jul	0.43	0.34	0.07	0.07	0.09	**10**
	Aug	0.50	0.36	0.05	0.04	0.05	**11**
	Sep	0.52	0.37	0.05	0.03	0.03	**12**

Table 29: The average table of ten health status trials for the Experiment II: Low-alarm

The final average chart represents the result of all the ten trials health status for Experiment II, Low-alarm.

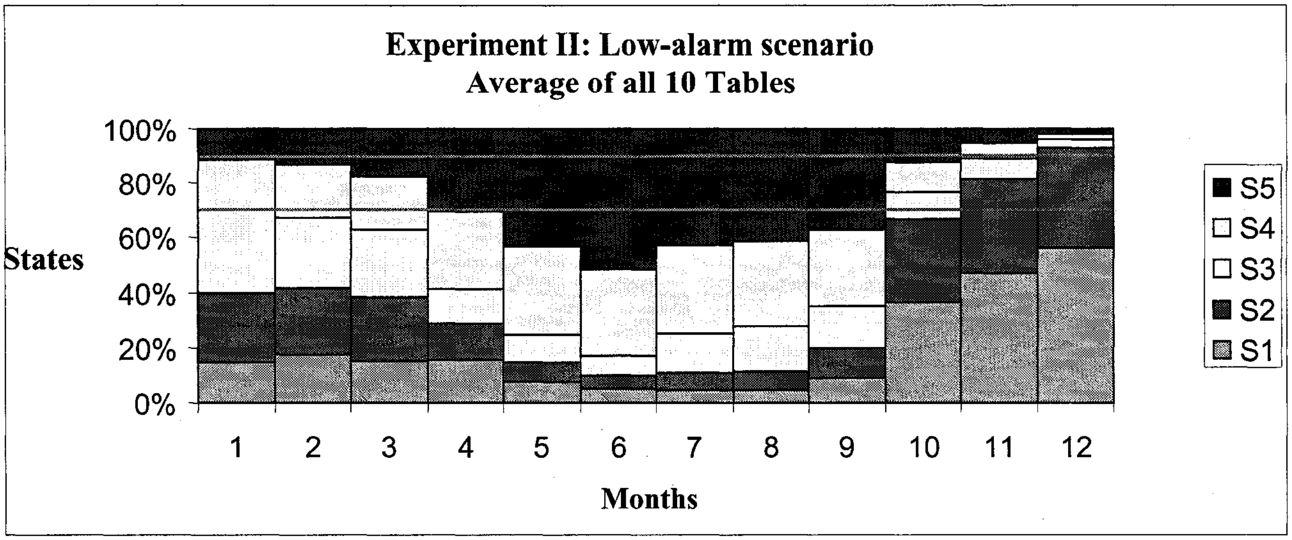


Figure 11: The average of all ten trials' graph for the Experiment II: Low-alarm

By comparing the graph of the average of the ten trials for the last two experiments, the Experiment I, No-alarm and the Experiment II, Low-alarm, little improvement on the S5 state of the obesity can be observed. The S5 estimate in some periods has reduced slightly, indicating an improved health status for the population. This demonstrates the slight advantage of using a more responsive alarm system.

5.4.3 Experiment III: Moderate-Alarm Model

The same procedure for the Experiment III, Moderate-alarm scenario was applied and the results are documented below. Table 30 presents the results for a single trial of the twelve months health status for the Experiment III: Moderate-alarm.

Experiment III. Moderate-alarm

States

		Fit & healthy	Average	Heavy	Overweight	Obese		
		S1	S2	S3	S4	S5		
	Oct	0.11	0.22	0.41	0.19	0.07	1	
	Nov	0.08	0.17	0.44	0.23	0.08	2	
	Dec	0.07	0.16	0.44	0.24	0.09	3	
	Jan	0.21	0.23	0.13	0.28	0.15	4	
	Feb	0.02	0.03	0.04	0.30	0.61	5	
Months	Mar	0.06	0.07	0.11	0.29	0.47	6	Periods
	Apr	0.02	0.04	0.07	0.30	0.58	7	
	May	0.01	0.03	0.06	0.30	0.60	8	
	Jun	0.02	0.03	0.12	0.37	0.46	9	
	Jul	0.59	0.35	0.02	0.02	0.01	10	
	Aug	0.45	0.40	0.10	0.03	0.02	11	
	Sep	0.64	0.33	0.02	0.01	0.00	12	

Table 30: The table of ten months health status for the Experiment III: Moderate-alarm

The result is also illustrated in the graph of Figure 12:

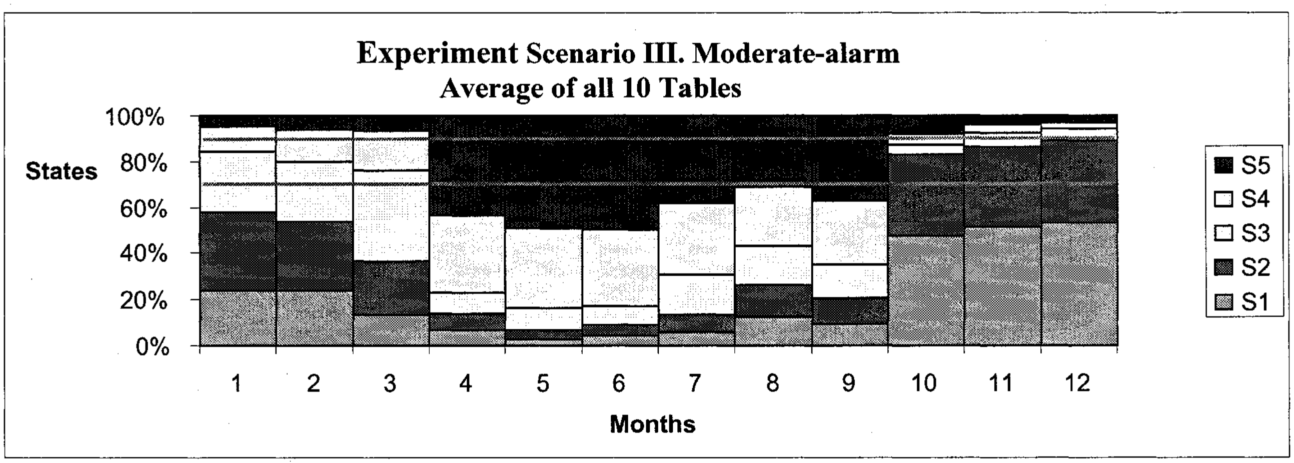


Figure 12: The graph for the experiment III: Moderate-alarm scenario

By repeating the exercise for ten randomly generated actual state transitions and observation monthly trials, the corresponding graphs are found in Appendix 2 (Experiment III: Moderate Alarm Trials).

Averaging all ten final health status trials and putting them in one single table, Table 31 is obtained for Experiment III, Moderate-alarm:

Experiment III: Moderate-alarm

States

Months		Fit & healthy S1	Average S2	Heavy S3	Overweight S4	Obese S5	Periods
	Oct	0.15	0.24	0.31	0.20	0.10	**1**
	Nov	0.18	0.26	0.30	0.17	0.09	**2**
	Dec	0.18	0.26	0.28	0.17	0.11	**3**
	Jan	0.09	0.09	0.13	0.34	0.36	**4**
	Feb	0.09	0.08	0.08	0.29	0.46	**5**
	Mar	0.06	0.05	0.08	0.32	0.49	**6**
	Apr	0.14	0.16	0.17	0.24	0.28	**7**
	May	0.13	0.14	0.15	0.25	0.33	**8**
	Jun	0.09	0.11	0.22	0.29	0.29	**9**
	Jul	0.37	0.30	0.09	0.10	0.14	**10**
	Aug	0.54	0.34	0.04	0.03	0.05	**11**
	Sep	0.55	0.37	0.04	0.02	0.02	**12**

Table 31: The table of ten health status trials average for the Experiment III: Moderate-alarm

The final average chart illustrated in Figure 13 represents the results of all the ten trials of health status for the Experiment III, Moderate-alarm.

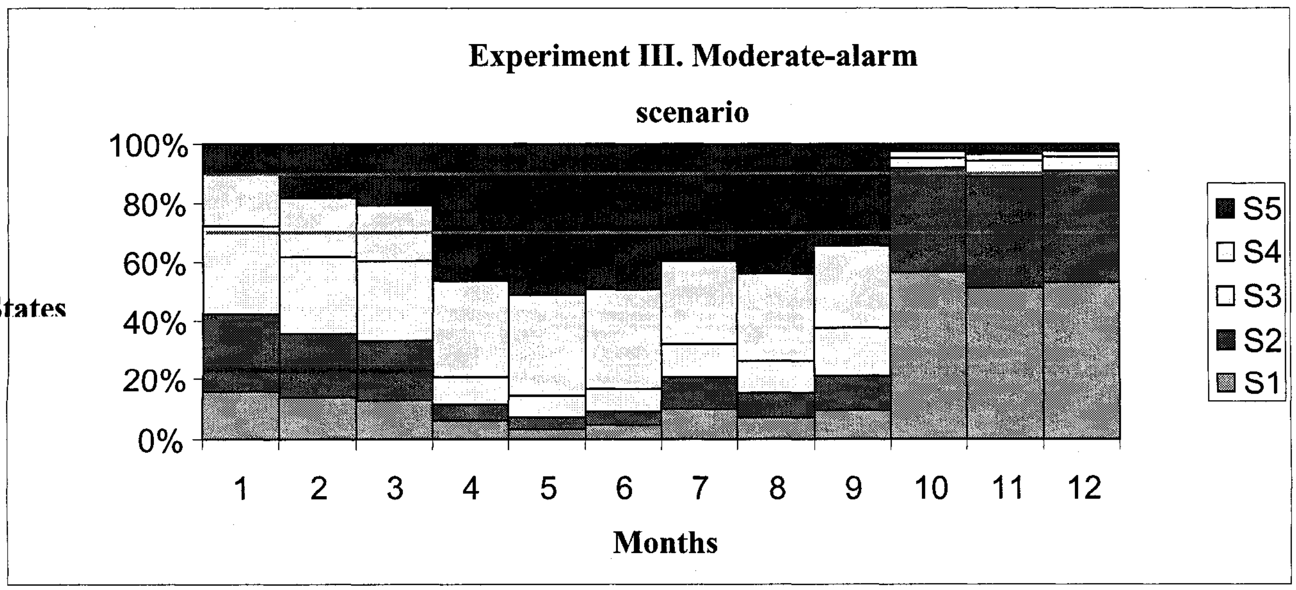


Figure 13: The graph of the average of all ten trials for the Experiment III: Moderate-alarm

Comparing the average graph for the last three Experiments (No-alarm, Low-alarm and Moderate-alarm scenarios), an obvious improvement on the S5 state estimate of the obesity is observed. The S5 estimate in Experiment III has declined sharply compared to a No-alarm scenario and it has improved slightly compared to the average results for Experiment II. This demonstrates the population health advantage of using the Moderate-alarm system over a Lower-alarm case.

5.4.4 Experiment IV: Extensive-Alarm Model

The final results for Experiment IV, Extensive-alarm scenario is given in this section. Table 32 demonstrates the results of a single trial of the twelve months health status for the Experiment IV: Extensive-alarm.

Experiment IV: Extensive-alarm

		States					
		Fit & healthy	**Average**	**Heavy**	**Overweight**	**Obese**	
		S1	**S2**	**S3**	**S4**	**S5**	
Months	**Oct**	0.10	0.15	0.28	0.29	0.17	**1**
	Nov	0.07	0.11	0.28	0.28	0.26	**2**
	Dec	0.10	0.18	0.37	0.20	0.15	**3**
	Jan	0.03	0.03	0.11	0.35	0.49	**4**
	Feb	0.02	0.04	0.14	0.45	0.34	**5**
	Mar	0.19	0.19	0.12	0.33	0.18	**6**
	Apr	0.13	0.14	0.29	0.25	0.19	**7**
	May	0.11	0.14	0.30	0.27	0.18	**8**
	Jun	0.08	0.08	0.16	0.32	0.36	**9**
	Jul	0.56	0.34	0.04	0.03	0.03	**10**
	Aug	0.72	0.27	0.00	0.00	0.00	**11**
	Sep	0.74	0.26	0.00	0.00	0.00	**12**

Periods

Table 32: The table of ten months health status for the Experiment IV: Extensive-alarm

The results of Table 32 are also demonstrated in Figure 14.

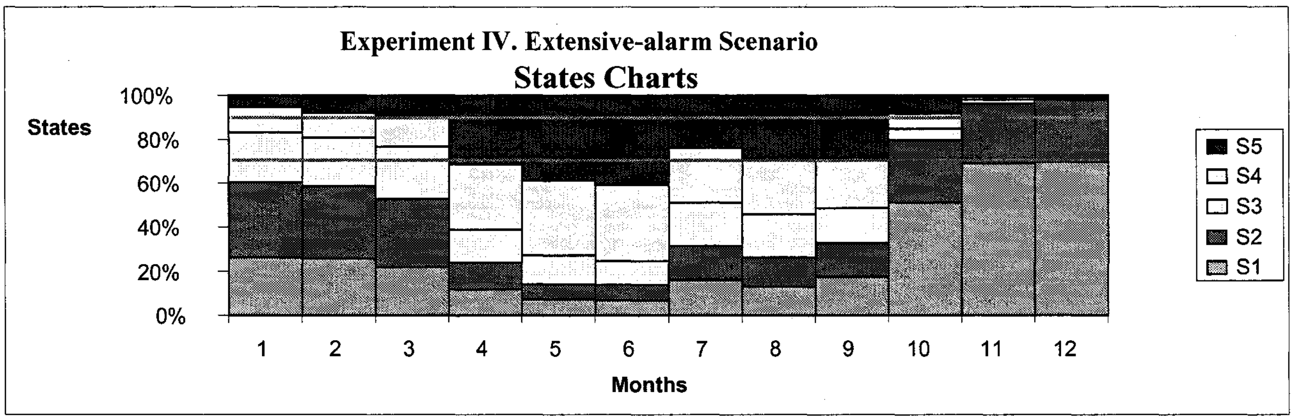


Figure 14: The graph for the Experiment IV: Extensive-alarm scenario.

Repeating the exercise for ten randomly generated actual state transitions and observation monthly trials, yields the results and corresponding graphs found in Appendix 2 (Experiment IV: Extensive Alarm Trials).

By averaging all of the ten final health status trials, and putting them in one single table, the following average table (Table 33) is obtained in the Experiment IV, Extensive-alarm:

Experiment IV: Extensive-alarm (Average)

	States					
	Fit & healthy	Average	Heavy	Overweight	Obese	
Months	S1	S2	S3	S4	S5	Periods
Oct	0.20	0.30	0.25	0.15	0.09	**1**
Nov	0.20	0.27	0.25	0.15	0.12	**2**
Dec	0.21	0.30	0.25	0.13	0.12	**3**
Jan	0.09	0.08	0.12	0.32	0.40	**4**
Feb	0.07	0.06	0.09	0.34	0.43	**5**
Mar	0.04	0.04	0.07	0.34	0.52	**6**
Apr	0.15	0.15	0.16	0.25	0.28	**7**
May	0.32	0.24	0.12	0.14	0.18	**8**
Jun	0.33	0.26	0.14	0.12	0.15	**9**
Jul	0.64	0.28	0.03	0.03	0.03	**10**
Aug	0.73	0.26	0.00	0.00	0.00	**11**
Sep	0.71	0.28	0.00	0.00	0.00	**12**

Table 33: The table of ten health status trials average for the Experiment IV, Extensive-alarm

The final average chart illustrated in Figure 15 represents the average results of all the ten trials of health status for Experiment IV, Extensive-alarm.

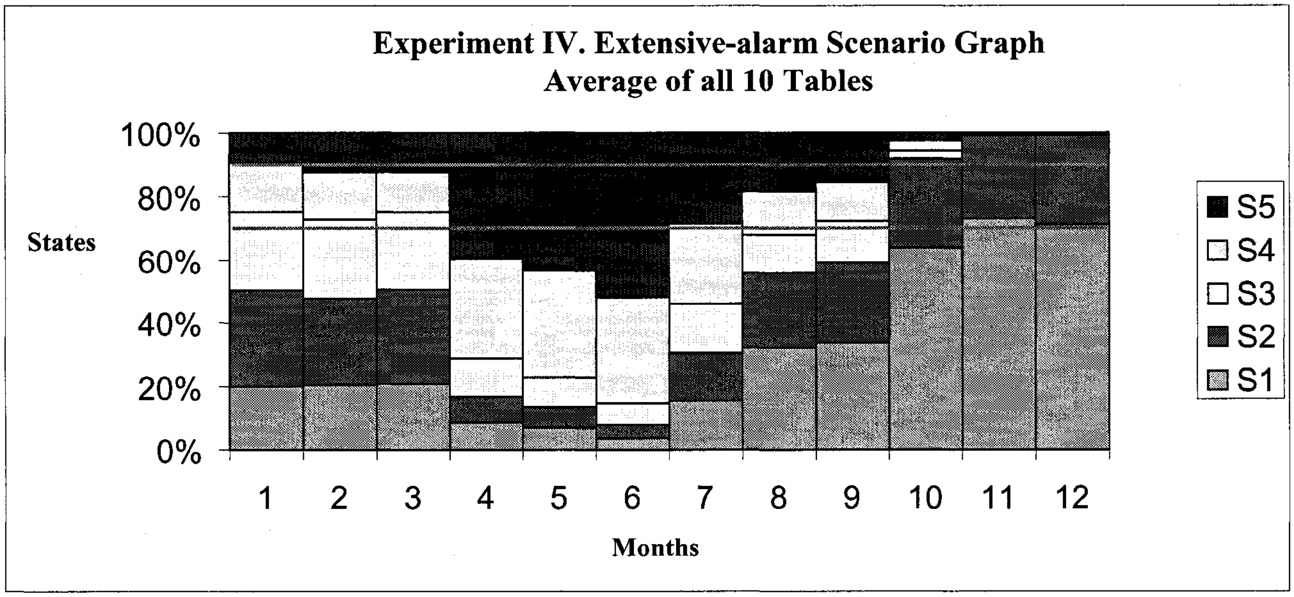


Figure 15: The graph of the average of all the ten trials for the Experiment IV: Extensive-alarm

By comparing the graph of the average of all the ten trials for the last four Experiments (No-alarm, Low-alarm, Moderate-alarm and Extensive–alarm), a sharp improvement of the S5 state of obesity from Experiment IV, Extensive–alarm, can be observed. The S5 estimate in Experiment IV has been reduced sharply compared to the other experimental results. As it can be observed in Figure 15, the S5 has disappeared in the two months of August and September and, instead, the state of the Fit & healthy, (S1), has advanced exclusively in last five months of the year. This demonstrates the potential health advantage of the Extensive-alarm system compared to the other intevention strategies.. However, while the potential effect of more intensive health interventions are obvious, health improvements must also take into account the cost of the interventions in order to construct viable health policy strategy. The costs results of these experiments are modelled for decision making purposes in the next section.

5.5 Experimental Conclusions

The previous section showed the results of all four different experiments:

I. No-alarm (Baseline)

II. Low-alarm

III. Moderate-alarm

IV. Extensive-alarm

By comparing the results of the modeled experiments, it is observed that as the level of alarms is elevated, the health status in terms of the probability estimates in heavy (S3), overweight (S4) and obese (S5), are also improved, i.e. reduced. In other words, the Extensive-alarm model has a higher area of improvement in S3, S4, and S5, compared to the experimental results for the Moderate-alarm. Similarly, the Moderate-alarm shows an improvement in compared to the Low-alarm or No-alarm models. From a probabilistic perspective, as expected, the system of policy implementation based on higher levels of alarms improves the health status and obesity state measures. (See Appendix 3 for details on comparison results)

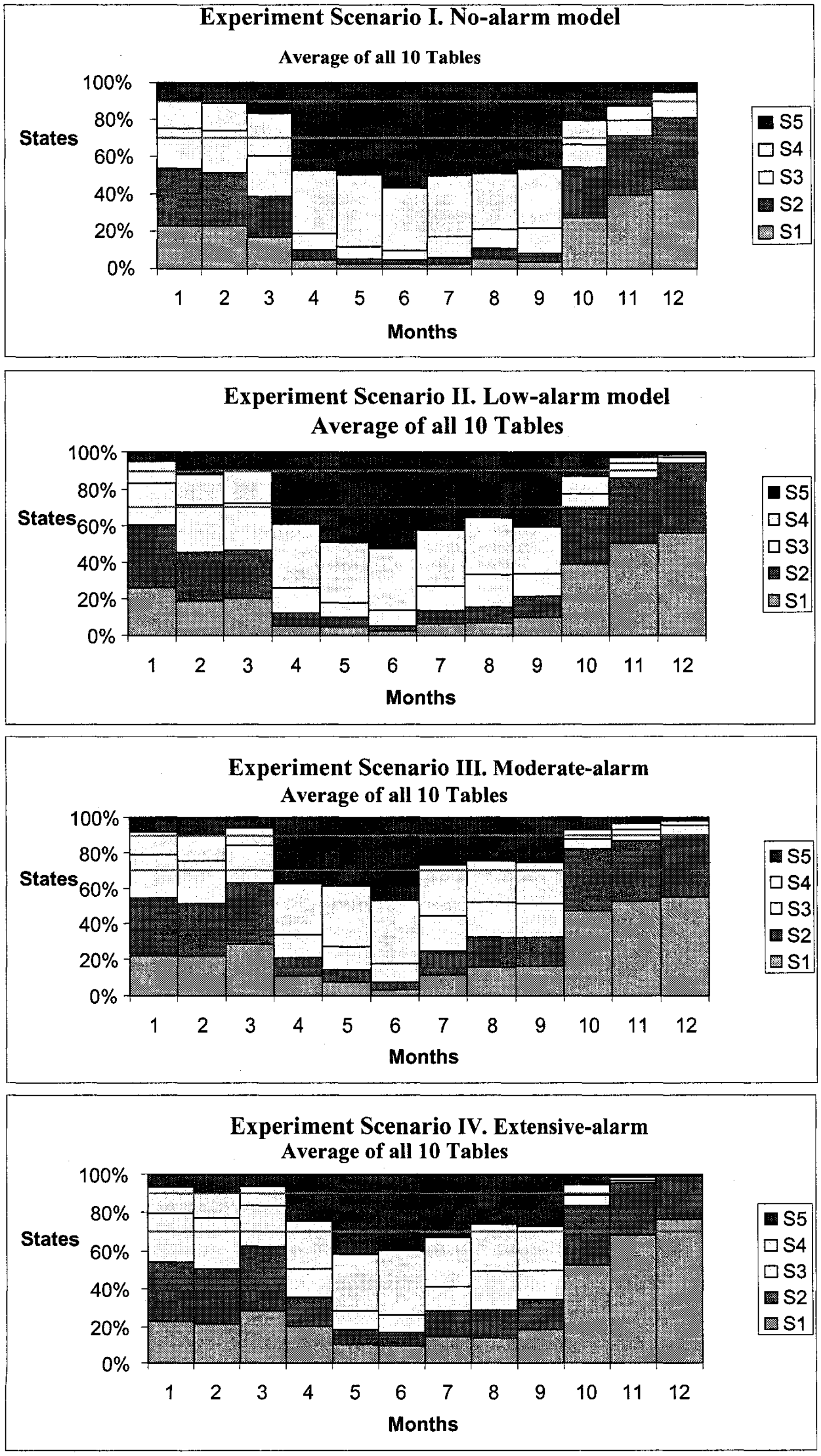


Figure 16: Demonstration of graphs for all the four experiments

While the experimental simulation in all four models conclusively demonstrated the advantages of using alarms and policy implementations, the economic cost of these interventions needs to be analyzed. The costs of using different types of alarms and policy interventions are not the same for the each experiment.

Initial results might suggest that the No-alarm model with no policy intervention has lower (i.e., zero) intervention costs in comparison with the other strategies. The improvement of health status and the reduced cost of dealing with obesity from higher levels of alarms however could save health care costs and bring overall costs down. In order to investigate the cost implications of alternative policies, a simple decision analysis method is carried out to calculate the best expected value decision for lowering total costs. Decision tree analysis is used to illustrate this in the next section.

5.5.1 Decision Analysis

Decision analysis plays an important role in finding a cost efficient policy intervention method. Decision tree analysis is used to determine the minimum total expected cost scenarios. The expected value of each scenario is calculated by estimating the cost of each strategy and its related costs of policy intervention for the No-alarm strategy, the Low-alarm, Moderate-alarm, and Extensive-alarm strategies. It is assumed that there is a monthly cost of maintaining the population in each health status.

Different health status measures have their own health related costs in the population. Obviously, a healthier population has a lower monthly health maintenance cost compared to the more costly unhealthy population. Obesity, State S5, has the highest monthly maintenance costs within the health system. Taking into account all of the above related cost issues, the four intervention policies are compared to find the expected annual costs minimal policy as described in the next section.

5.5.2 Cost Analysis

Cost is an important factor for any decision-making strategy. The analysis and evaluation of the intervention strategies includes the costs attached to each experiment. Based on data estimated from

Health Canada statistics, the costs related to each population health status can be estimated and applied to evaluate the periodic cost impacts of each intervention and subsequent health states. For this cost estimation, the population is based on the latest statistical data where Canada's population was estimated to be 33,098,932 in July 2006 (CIA, 2007).

The Fraser Institute in December 2006 forecasted that heath care spending in Canada for 2006 was $148 billion, or $4548 per person (Esmail, 2006). The 2007 report by the same institute reports that average per-capita provincial/territorial health spending in Canada was about $2,630 in 2004. This spending for Canadian, aged 65 to 74, was about $5,865, and for aged 75 to 84 was roughly $10,342, and on those 85 years of age and older was $19,418, based on CIHI, 2006 (Skinner, B. and Rovere, M. 2007). The cost of obesity-related diseases in the Canadian health care system could be very high, however, the precise cost of obesity and its related diseases are unknown. Based on the Fraser Institute information, however, it is assumed to be $2000 per person per year. This estimated health cost is used to determine the attributable Canadian population health cost in a year related to the current analysis on obesity (and excluding other health costs not related to the active population), as follows:

Health Care Cost / person/Year:	$2000 (based on $4548/person/year)
Health Care Cost / Population/Year:	$2000 x 33,098,932 = $66,197,864,000
Health Care Cost / Population/month:	$66,197,864,000 ÷ 12 = $5,516,488,667

Based on this estimate, the monthly maintenance health cost across the Canadian population is $5.5 billion. Since the degree of obesity is different within the population, this cost is distributed among that population. Table 34 shows how the monthly maintenance health costs are attributed to each health care state. The scale is based on the obesity Health Care Cost (HCC) per total population per month:

	HCC/Pop/m	Assumed Portions /Scale	Round value per Million
Fit & healthy	**$5,516,488,667**	**0.25**	**$1,379**
Average	**$5,516,488,667**	**0.55**	**$3,034**
Heavy	**$5,516,488,667**	**1**	**$5,516**
Overweight	**$5,516,488,667**	**2**	**$11,033**
Obese	**$5,516,488,667**	**4**	**$22,066**

Table 34: The scale of the obesity Health Care Cost (HCC) per total population per month

Therefore the estimated cost is defined in a vector (Table 35) as follows:

S1	S2	S3	S4	S5
Fit & Healthy	Average	Heavy	Overweight	Obese
$1,379	$3,034	$5,516	$11,033	$22,066

Table 35: Obesity and its health costs estimates

Cost estimates are used to evaluate the effective health status costs implicated by the health policy over the 12 months in each trial. Monthly probability estimates for each state are used to attribute the relative health costs. As such, alternative health intervention strategies and results can be compared to advice health policy.

Total annual policy costs include: (1) the annualized cost of the monthly health status maintenance, and, (2) the costs of policy health interventions in the course of the year. These are described in further detail below. (See Appendix 4 for details on cost analysis). The annual alarm or policy intervention cost depends on the intervention level (low, moderate, or extensive) that may occur in each month and the unit costs of each intervention. The cost of each alarm intervention is estimated to be a quarter of each of the S3 (Heavy) maintenance costs, the S4 (overweight) maintenance costs, and the S5 (obese) maintenance costs, for each intervention, i.e.,

Alarm type #1 (Low-alarm) monthly costs: S3/4 = $5,516/ 4 = $1,379
Alarm type #2 (Moderate-alarm) monthly costs: S4/4 = $11,033/ 4 = $2,758
Alarm type#3 (Extensive-alarm) monthly costs: S5/4 = $22,066/4 =$ 5,517

Therefore, by knowing the total number (months) of each alarm's occurrences in one year, the total cost of using alarms can be calculated. Table 36 demonstrates the total cost of alarms in a year in the Experiment IV extensive intervention scenario.

	Total Alarm 1	Total Alarm 2	Total Alarm 3
Trial # 1	0	1	8
Trial # 2	1	1	8
Trial # 3	3	1	8
Trial # 4	1	2	9
Trial # 5	0	1	9
Trial # 6	2	1	9
Trial # 7	1	1	8
Trial # 8	0	1	8
Trial # 9	1	1	10
Trial # 10	1	1	8
SUM:	10	11	85
X	1379	2758.25	5516.5
=	Total Alarm 1	Total Alarm 2	Total Alarm 3
Sub-Total	13790	30340.75	468902.5

=

Total Alarm costs:	
Trial # 1	46890.3
Trial # 2	48269.3
Trial # 3	51027.3
Trial # 4	56544
Trial # 5	52406.8
Trial # 6	55164.8
Trial # 7	48269.3
Trial # 8	46890.3
Trial # 9	59302.3
Trial # 10	48269.3
Total:	513033

Total Alarms' cost:
513033.25

Table 36: Demonstration of total alarm costs in an extensive intervention scenario

Based on the same health maintenance cost vector for each intervention, the total annual health cost can be calculated. (See Appendix 4 for details on cost analysis.)

The final total health costs are added to the final cost of the alarms in every single trial in every scenario for comparison. Then the total health cost (monthly maintenance and intervention) of each trial can be calculated as in Table 37 for 10 independent trials of each experiment.

Alarm Cost	Trial #1	Trial #2	Trial #3	Trial #4	Trial #5	Trial #6	Trial #7	Trial #8	Trial #9	Trial #10	Total
I. No-alarm model	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00
II. Low-alarm model	$9,653.75	$9,653.50	$15,170.25	$19,307.50	$13,790.75	$11,032.75	$11,032.75	$17,928.25	$19,307.75	$9,653.75	$136,531.00
III. Moderate-alarm	$16,549.50	$22,066.00	$13,791.00	$19,307.75	$15,170.25	$16,549.50	$26,203.25	$15,170.25	$22,066.00	$24,824.25	$191,697.75
IV. Extensive-alarm	$53,785.75	$51,027.25	$51,027.25	$53,785.75	$48,269.25	$46,890.25	$46,890.25	$51,027.25	$55,164.75	$48,269.00	$506,136.75
Health Cost	**Trial #1**	**Trial #2**	**Trial #3**	**Trial #4**	**Trial #5**	**Trial #6**	**Trial #7**	**Trial #8**	**Trial #9**	**Trial #10**	**Total**
I. No-alarm model	$122,563.33	$139,380.83	$131,280.69	$107,519.18	$127,272.02	$92,514.04	$127,018.14	$122,981.88	$103,947.42	$105,841.49	$1,180,319.03
II. Low-alarm model	$102,222.69	$91,808.52	$122,536.41	$132,346.76	$108,137.60	$95,634.37	$96,195.07	$134,946.65	$134,853.67	$98,974.84	$1,117,656.58
III. Moderate-alarm	$94,530.68	$131,340.08	$106,826.86	$109,561.96	$107,839.61	$109,739.12	$134,371.72	$100,349.84	$107,431.66	$130,493.82	$1,132,485.37
IV. Extensive-alarm	$108,829.70	$102,333.36	$105,699.31	$118,165.50	$110,008.57	$100,474.26	$87,696.72	$94,604.06	$120,145.04	$111,668.68	$1,059,625.22
Total Cost	**Trial #1**	**Trial #2**	**Trial #3**	**Trial #4**	**Trial #5**	**Trial #6**	**Trial #7**	**Trial #8**	**Trial #9**	**Trial #10**	**Total**
I. No-alarm model	$122,563.33	$139,380.83	$131,280.69	$107,519.18	$127,272.02	$92,514.04	$127,018.14	$122,981.88	$103,947.42	$105,841.49	$1,180,319.03
II. Low-alarm model	$111,876.44	$101,462.02	$137,706.66	$151,654.26	$121,928.35	$106,667.12	$107,227.82	$152,874.90	$154,161.42	$108,628.59	$1,254,187.58
III. Moderate-alarm	$111,080.18	$153,406.08	$120,617.86	$128,869.71	$123,009.86	$126,288.62	$160,574.97	$115,520.09	$129,497.66	$155,318.07	$1,324,183.12
IV. Extensive-alarm	$162,615.45	$153,360.61	$156,726.56	$171,951.25	$158,277.82	$147,364.51	$134,586.97	$145,631.31	$175,309.79	$159,937.68	$1,565,761.97

Table 37: The table of health costs for four experiments and 10 independent trials for each.

A decision-making tree is used to find the cost minimizing experiment for each comparative trial run from 1 to 10. A final decision tree determines the final decision in each simulated trial run. (See Appendix 5 for details on cost decision)

5.5.3 Decision Tree

The previous section demonstrated the total cost in ten trials of all four Experiments (No-alarm, Low-alarm, Moderate-alarm and, Extensive-alarm scenarios), in a case study for the obesity example. By using a decision-making tree, the final costs for each experiment will be compared and a final decision for the cost minimizing strategy will be determined across all 10 trials. This final decision will be based on the lowest total cost. The results are based on simulated health status trials, where the outcome for each simulated trial may differ from other simulations. (See Appendix 5 for details on cost decision.)

Figure 17 shows the decision tree used for one of the 10 trials.

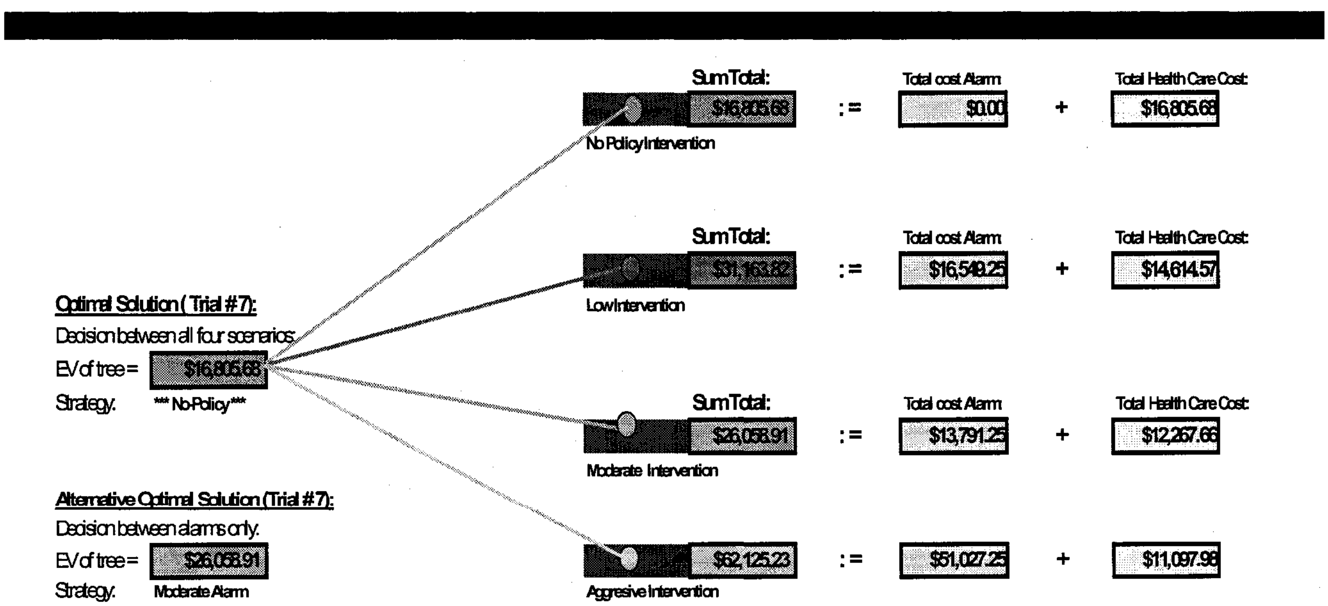


Figure 17: Demonstration of a decision tree in one example trial

Figure 18 demonstrates a decision tree where, the updated total health costs of all four different scenarios: No-alarm, Low-alarm, Moderate-alarm, and Extensive-alarm scenarios in Trial #7 are displayed. This decision tree adds the final costs of alarms and the health costs in the first trial and compares the total health costs with each other. The Experiment I, No-alarm model, is the lowest cost of all the four Experiments in this first trial. By considering an alternative optimal solution, the decision is made without considering the No-alarm scenario option. This alternative optimal solution favours the Low-alarm model as its lowest cost alternative option among the models with alarms. As a result, the best option is being introduced among the models with alarms only.

The results of the ten different decision trees for the ten different independent trials of the four Experiments, is summarized in Figure 18.

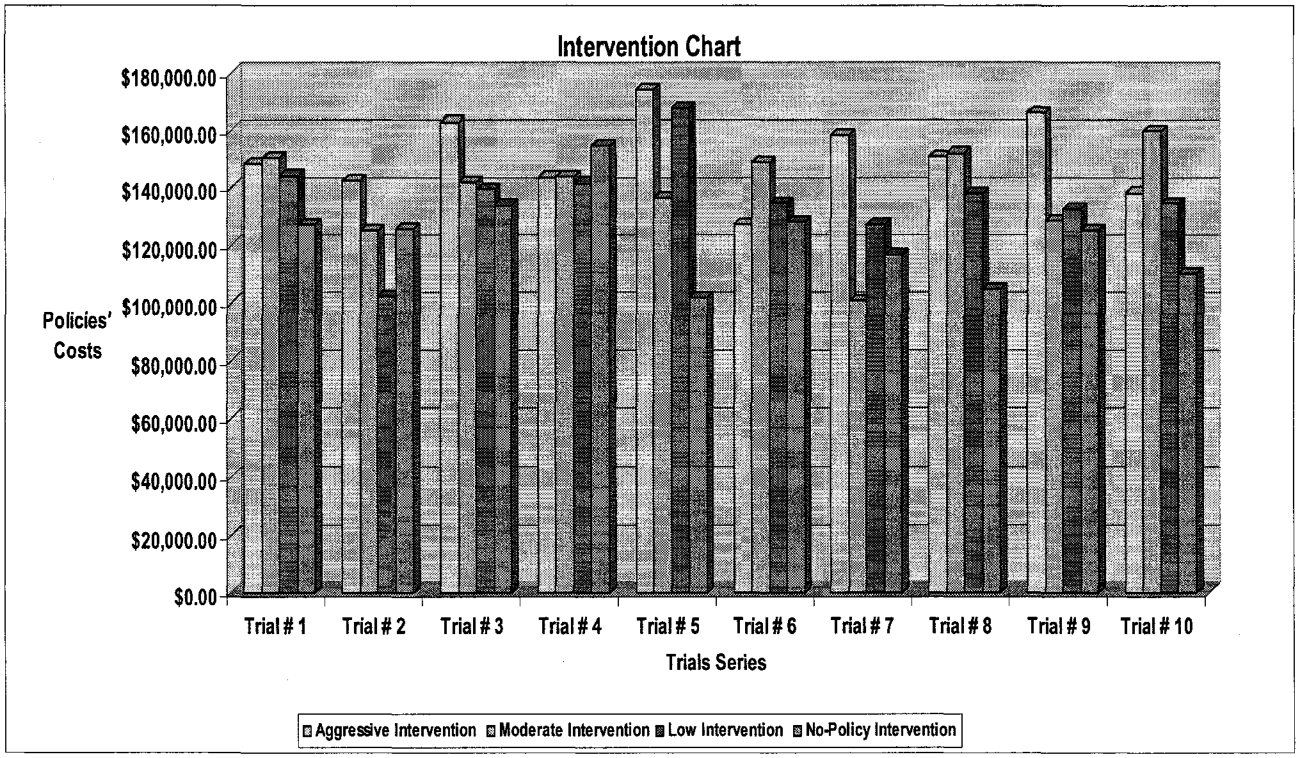


Figure 18: The cost related charts of each trial for all four experiment models.

Figure 18 shows the cost related charts of each trial for all four experiment models. It is obvious that the Experiment IV, extensive model has very high total costs compared with all the other experiments. The lowest cost, in most cases, is the Experiment I, No-alarm or no policy intervention model. The result of the ranking of each experiment may vary in each simulation.

A final decision tree adds the total alarm costs and the health costs of all the Experiments. The results are finalized in one single decision tree to find an optimal solution with an alternative case solution similar to the single trial decision trees. The final decision tree, as shown in Figure 19, is based on the total cost in all trials. The total (or averaged) cost results yield the same cost minimizing decision options as noted in trials (#2,5 and 9) of Figure 18 and for the single trial described in Figure 17.

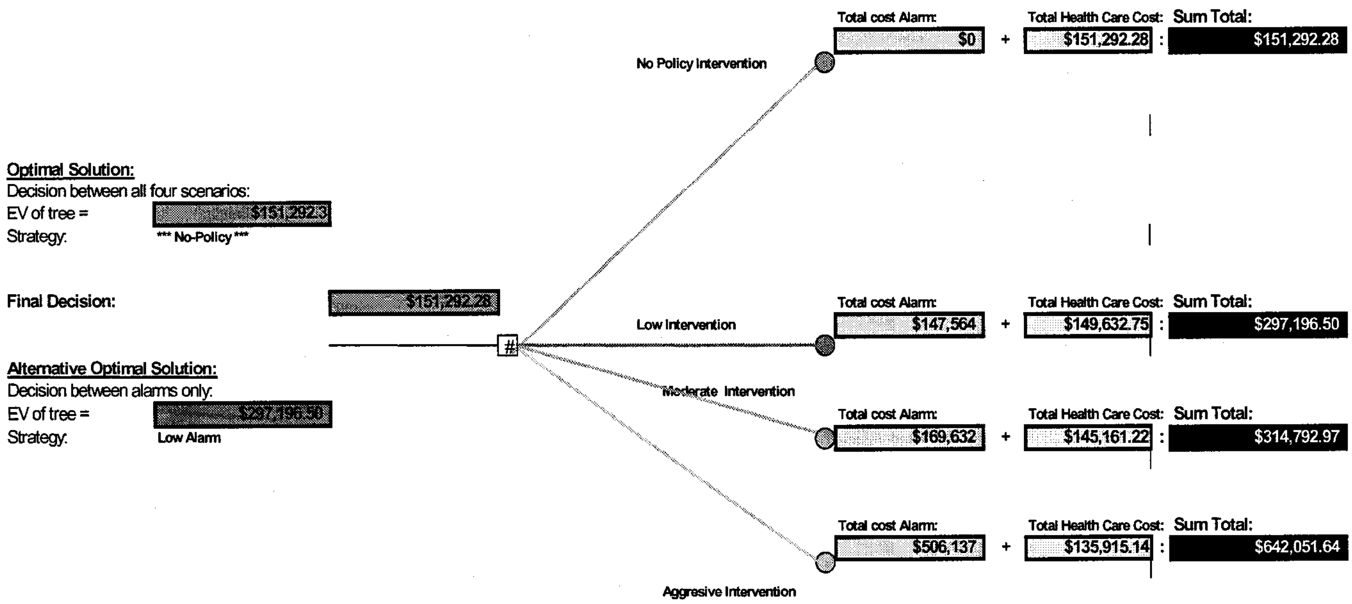


Figure 19: Decision tree for total costs over all ten trials.

This chapter presented an application for the proposed post-market surveillance model as an example related to the GM foods. It is an application in which the post-market surveillance is required to access evidence for the advantages and disadvantages of policy implementation as a control mechanism. The case evaluated how obesity impacts specific aspects of the health status of a population and how alarms and triggered policy interventions can be made to respond to declining health observations in a partially observable system. The health status focused on the important issue of population obesity as a possible side effect of consumption of foods attributed to the obesity problem, e.g., including fatty food, complex carbohydrates, and modified foods. The report illustrated a hypothesis that the consumption of complex and modified food products, may contribute to an increase of obesity in a population.

The obesity problem in our population is recognized as a partially observable system, given the effective lack of surveillance systems in place and the absence of reliable prevention policies. The following sections discuss the application of the post-market surveillance model to the obesity health issue by attributing surveillance and control to policy interventions.

6. Conclusions

The post-market surveillance of a partially observable system may play a critical role for public safety and a healthy economy in an open market system, where there are no major restrictions and limits for new technologies, imports and exports. A post-market surveillance model with close observation of new, controversial products, could improve a constrictive and flexible market policy.

This paper introduces a model for the analysis of partially observable information from the post-market surveillance. This model uses Markov Chains together with a Bayesian updating function to estimate the statistical impacts of surveillance observations and modified surveillance policies.

Alarms and different levels of policy implementation are unique in this research model. Flexibility with market demands and adjustability with cost analysis and cost decisions are the advantages of this post-market surveillance model. It is concluded that the demonstrated model can be used for a complex partially observable system to have a clear observation on most controversial products.

The results of the experimental analysis using illustrative data between cost decisions and policy implementation decisions indicate that lower or moderate health policy interventions may be a more worthwhile choice to improve a health system scenario compared with no interventions, or simply waiting for a crisis to occur before acting. The extent to which cost tradeoffs are defined would more clearly rank these alternative actions.

6.1 Recommendations for Future Research

There is also a need for a reliable data collection and analysis for deciding on states, transition matrices, and reliability matrices data. In this paper, all the logical data, transition matrices, and reliability matrices information and values are based on logical assumptions and probabilities rather than a direct causal link that frankly, in many cases, such a GM foods, has been very difficult to define. It is argued that the developed and illustrated health strategy model is useful if there is a still more reliable data collection mechanism designed to suit the probabilistic and reliability measure of actual data.

Some of the problems with data collection and analysis for deciding on status of a health system are the absence of a method to standardize our health systems that collect health information, to build an integrated database for each health status, to strengthen the capacity for running the systems (e.g., number of staffs, technicians,...), and to minimize the cost. Without adequate information systems to manage health data, the actual health state of a given population, and its observation could be illusive. As a result, there might be cases of miss management to assign appropriate priorities and delegate services for our health system.

The surveillance and monitoring of products is not an easy task. It requires national and international efforts to achieve an understandable and clear picture about its true nature, to be able to draw conclusions whether to reject or to support such products. Any policy to control or to ban a product can have an impact on local and international trade relationships.

There is a need for an international cooperation to share information and to control and observe such products. If such a protocol will come into effect, there is a need for national and international policy changes. This policy should be in respect to all economical, political, social, and environmental angles. There is a need to have better surveillance on GM products and to observe its impact on short and long term local and international macro and micro economy.

In this model, using an appropriate and accurate data is crucial to assign right values on health states, vectors, transition matrices, and reliability matrices for obtaining an appropriate outcome and moving towards making valid decisions analysis.

7. Bibliography

Amanor-Boadu, V. Amanor-Boadu, Y. 2002. The Post-Market Surveillance of potential Human Late health effects of Genetically Modified foods' initiatives: Lessons for Canada's Strategy. Publisher: AgriFood Innovations, Health Canada.

Barnes, D. Campbell, K. Sampson, M. Schachter, H. Baker, J. Moher, D. 2002. Post-Market Surveillance of Biotherapeutics for Late Health Effects- A Systematic Review and Recommendations on active Surveillance in Canada. International Conference on post-Market Surveillance of Genetically Modified Foods, 8p.

Baynton, C. 2002. The feasibility of post-market monitoring of genetically modified foods, International Conference on post-Market Surveillance of Genetically Modified Foods, 65p.

Beckman, C. 2005. Soybeans: Situation and Outlook, Agriculture and Agri-food Canada publication, 2005-04-29, Volume 18 Number 8, ISSN 1494-1805, AAFC No. 2081/E

Birmingham, C. 1999. The cost of obesity in Canada. Canadian Medical Association Journal. 160(4); Pages 503-513.

Center for Surveillance Coordination, 2002, "The Journey to Here: Post-Market Surveillance of Late Human Health Effects and Health Canada." International Conference on Post-Market Surveillance of Genetically Modified Foods; Pages 217-223

Dewar, D. 2002. The Feasibility of Post-Market Surveillance. International Conference on post-Market Surveillance of Genetically Modified Foods, 10p.

Finlay, K., Sheeshka, J. 2002. International conference on Post-Market Surveillance of Genetically Modified Foods: Consumers' Perspectives on Trust in Government and Post-Market Surveillance of GM Foods. Publisher: Center for Surveillance Coordination, Health Canada, 11p.

Finkelstein, E., Fiebelkorn, I. & Wang, G. 2004. State-level estimates of annual medical expenditures attributable to obesity. Obesity Research. 12(1); Pages 18-24.

Friel, S. 2002. International conference on Post-Market Surveillance of Genetically Modified Foods: Nutrition Surveillance in the Republic of Ireland, 107p.

Health Canada, 2003. The Post-Market Surveillance of Bio-engineering Pharmaceuticals. Page 8-12.

Health Canada, 2004. Population and Public Health Branch, A Discussion on the post-market Surveillance of Food.

Kirkey, S. 2006. Feeding an obesity epidemic, Ottawa Citizen. Nov 21st 2006, A1p.

Katzmarzyk, P. 2002. The Canadian obesity epidemic, 1985-1998. Canadian Medical Association Journal. 164(8); 1039-40.

Lane, D. 1989. Operational research and fisheries management. European Journal of Operational Research. Volume 42, Issue 3 (October), pages 229-242.

Taylor, H. Lane, D. Michalowski, W. 2004. A Framework for Evaluating a Novel Food Regulatory Toolkit, Working Paper

Maryanski, J. 2002. A Brief Look At FDA's Experience with Post-Market Monitoring of Foods, International Conference on Post-Market Surveillance of Genetically Modified Foods, 21p.

Mendelssohn, R. and Sobel, M.J.1980. Capital Accumulation and the Optimization of Renewable Resource Models. J.Econ. Theory 23, 243-260.

Mendelssohn, R. and Sondik, E.J.1979. The cost of information seeking in the Optimal Management of Random Renewable Resources. Southwest Fisheries Center Administrative Report H-79-12, U.S.

National Oceanic and Atmospheric Administration. National Marine Fisheries Service, Honolulu, HI.

Monahan, G. E. 1982. A Survey of partially Observable Markov Decision Processes: Theory, Models and Algorithms. Mgmt. Sci. 18, 362-380.

Mowat, D. Amanor-Boadu, V. 2002. A Framework for Estimating Health Value of Post-Market Surveillance of GM Food. International Conference on post-Market Surveillance of Genetically Modified Foods. 48p.

Spiegelhalter, D. Abrams, K. Myles J. Bayesian Approaches to Clinical Trials and Health-Care Evaluation, 2004. Published by John Wiley and Sons, 2004, 391 pages, Pages 1-13.

Statistics Canada. 1999b. Health Reports. (Summer 1999). Vol. 11(1). Catalogue no. 82-003-XIE.

Statistics Canada. 2003b. Food Statistics 2002. Vol. 2(1&2). Catalogue no. 21-020-XIE.

Statistics Canada. 2007b. Cereals and Oilseeds Review Series Cat. No. 22-007, May 29, 2007

Smallwood, R.D., And Sondik E.J.1973. The Optimal Control of Partially Observable Markov Processes over a Finite Horizon. Opns. Res. 21, 1071-1088

Sondik, E.J & Mendelssohn, R.1979. Information Seeking in Markov Decision Processes. Southwest Fisheries Center Administrative Report H-79-13, U.S. National Oceanic and Atmospheric Administration. National Marine Fisheries Service, Honolulu, HI.

Wassell, P. Young, N.W.G. 2006. Food applications of trans fatty acid substitute, International Journal of Food Science and Technology, Volume 42, Pages 503-517.

WHO, 1946. National Mental Health Policy, Constitution of the World Health Organization, 20p.

8. Web References

Agriculture and Agri-food Canada, 2005. Soybeans: Situation and Outlook

http://www.agr.gc.ca/mad-dam/index_e.php?s1=pubs&s2=bi&s3=php&page=bulletin_18_08_2005-04-29

Agrifood Awareness Australia, 2001. StarLink™ Corn in the U.S.

http://www.afaa.com.au/pdf/18-StarLink.pdf

Agovino, T. 2004. Merck Faces Huge Fallout over Vioxx Suits, The Associated Press, Nov 2004

http://msnbc.msn.com/id/6410752/from/RL.1/#storyContinued

http://www.drugrecalls.com/News_Archive/Vioxx_News/vioxx_news_2004_11_05_1.html

Alberta Government. 2004. Department of Agriculture, Food and Rural Development April 2004

http://www1.agric.gov.ab.ca/$department/deptdocs.nsf/all/sis8438

Annis, C. 2007. Department of Statistical Engineering, Bayesian Updating

http://www.statisticalengineering.com/bayesian.htm

Australia New Zealand food authority (ANZEF). 2000. GM foods and the consumer, June 2000

http://www.foodstandards.gov.au/_srcfiles/gm_and_consumer_pub02_00.pdf

Berenson, A. 2006. Merck Loses Vioxx Suit in Texas,

http://www.nytimes.com/2006/04/22/business/22vioxx.html?ex=1182571200&en=af986d670c23d83d&ei=5070

Brinn L.2006. Study Examines Pharmaceutical Spending On Post-Approval Drug Safety,

http://www.fuqua.duke.edu/news/faculty/ridley-spending-0306.html

http://www.genomicglossaries.com/content/drugsafety.asp

Casati M, Picca M, Marinello R, Quartarone G., Aug 2007. Minerva Pediatr , 59(4):315-25.
Source: PubMed website viewed on Jan 22th, 2008 at 7:20 pm

http://www.ncbi.nlm.nih.gov/pubmed/17947838?ordinalpos=3&itool=EntrezSystem2.PEntrez.Pubmed.Pubmed_ResultsPanel.Pubmed_RVDocSum

CIA, 2007. The World Face Book: Canada
https://www.cia.gov/library/publications/the-world-factbook/geos/ca.html

Coghlan, A. 2004. "GM wheat put on hold", NewScientist.com.
http://www.newscientist.com/article.ns?id=dn4977

Collegeboard, 2008. "Epidemiology Glossary", visited the site on Jan 10th, at 5:30 pm.
http://www.collegeboard.com/yes/ae/gloss.html.

Daniells, S. 2007. Danisco explores future of trans fat alternatives.
http://www.foodanddrinkeurope.com/news/ng.asp?n=75895-danisco-trans-fatty-acids-cvd-allanblackia

Dr. Wan, H. 2006. GM Soya Fed Rats, Institute of Science In Society (ISIS), Nov 28th 2006.
http://www.i-sis.org.uk/GM_Soya_Fed_Rats.php

Dr. Rath Health Foundation. 2004. FDA too dependent on drug money, December 23, 2004
http://www4ru.dr-rath-foundation.org/THE_FOUNDATION/News/2004/pharmaceutical_business/index.htm

Dr. Kamsi, M.A. 2007. Markov Chain
http://www.sosmath.com/matrix/markov/markov.html

Dr. Keller, W. 2002. Standing Committee on Health, 37th PARLIAMENT, 1st SECTION
http://cmte.parl.gc.ca/cmte/CommitteePublication.aspx?COM=0&SourceId=15259&SwitchLanguage=1

Esmail, N. Walker, M. 2006. How Good Is Canadian Health Case? 2006 Report. Fraser Institute Digital Publication,
http://www.fraserinstitute.ca/admin/books/files/HowGoodHealthCare2006.pdf

Ethical Funds Company. 2006. Food for Thought. Pages: 26,27
http://www.ethicalfunds.com/do_the_right_thing/about_ef/newsroom/2006_articles/Sustainability%20Perspectives_GM%20Foods_Jun06.pdf

ETC Group Communiqué. 2005. Global Seed Industry Concentration, September 2005 Issue # 90
http://www.mindfully.org/Farm/2005/Global-Seed-Industry6sep05.htm

FAO (Food and Agriculture Organization of the United Nations). 1995. Dimensions of need
http://www.fao.org/docrep/U8480E/U8480E07.htm

Factsheet. 2001. Genetically Modified Crops in the U.S., August 2001.
http://pewagbiotech.org/resources/factsheets/display.php3?FactsheetID=1

Fulmer, M. 2001. "Biotech Bears Fruit for Farmers but What About Consumers?" Los Angeles Times,
http://www.biotech-info.net/bearing_fruit.html

GMAC. 2004. Genetic Modified Foods, April 2004
http://www.gmac.gov.sg/index.html

Genetically Modified Organisms, 2001. Molecular to Global Perspectives
http://www.learner.org/channel/courses/biology/pdf/13_gmo.pdf

Genetically modified food. 2005 . Wikipedia,
http://en.wikipedia.org/wiki/Genetically_modified_food#_note-16

Griffiths, H. 2006. Organic Consumer Association, New Book 'Genetically Modified Food, Aug 2006
http://www.organicconsumers.org/articles/article_1860.cfm

Gobbi, P. 2000. Brazil's hot debate over genetically modified foods, November 13, 2000
http://www.exploratorium.edu/theworld/gm/brazil.html

Golden Harvest Organics LLC. 2005. The Failure of the first GM Foods.

http://www.ghorganics.com/failure%20of%20the%20first%20GM%20foods.htm

Gondziola, J. Badger, G. 2005. New Roles, Confusing games
http://www.newcanadian.com/images/nov05/mag-sections/NEW%20ROLES.pdf

Hays, K. Easton, P. 2005. Jury Hung in First Federal Vioxx Trial, Associated Press Writers

http://www.chron.com/disp/story.mpl/ap/business/3518843.html

Hauskrecht, M. Fraser, H. 1998. Modeling Treatment of Ischemic Heart Disease with Partially Observable Markov Decision Processes

http://citeseer.ist.psu.edu/update/367188

Health Measurement Research Group, 2005. The National Health Measurement Study, Viewed on Jan 30th, at 6:30 pm.

http://www.healthmeasurement.org/NHMS.html

Health Canada. 2004. Genetically Modified (GM) Foods and Other Novel Foods.

http://www.hc-sc.gc.ca/fn-an/gmf-agm/index_e.html

Heath Canada. 2006. Health Protection Legislative Renewal

http://www.hc-sc.gc.ca/ahc-asc/pubs/legren/propos-f_e.html

Health Canada, 2006b. Healthy Canadians, A Federal Report on Comparable Health Indicators. Source viewed on Jan 29th at 2:30 pm

http://www.hc-sc.gc.ca/hcs-sss/alt_formats/hpb-dgps/pdf/pubs/2006-fed-comp-indicat/2006-fed-comp-indicat_e.pdf

Health Canada. 2007. The Progressive Licensing Framework

http://www.hc-sc.gc.ca/dhp-mps/prodpharma/activit/consultation/proglic_homprog_concept_e.html

Health Canada-B. 2007. Highlights of the Federal Regulatory Post-Market Surveillance Strategy http://www.hc-sc.gc.ca/ahc-asc/alt_formats/hpfb-dgpsa/pdf/pubs/highlights-oints_surveillance_e.pdf

Hull, J. 2007. Controversies In Nutrition. (Dr. Jannet Starr Hull) http://www.janethull.com/newsletter/1106/controversies_in_nutrition.php

Kleter, A. Krieken, W. Kok, E. Gilissen, L. 2001. Exploitation and regulation of plants genetically modified to express nutraceuticals and pharmaceuticals. http://www.agbios.com/docroot/articles/01-361-001.pdf

Locatelli F, Roger S., Oct 2006. Comparative testing and pharmacovigilance of biosimilars, Suppl 5:v13-6. Source: PubMed website viewed on Jan 25th, 2008 at 5:15 pm.

http://www.ncbi.nlm.nih.gov/pubmed/16959789?ordinalpos=27&itool=EntrezSystem2.PEntrez.Pubmed.Pubmed_ResultsPanel.Pubmed_RVDocSum

Maroni M, Fanetti AC, Metruccio F., April 2006. Risk assessment and management of occupational exposure to pesticides in agriculture, 97(2):430-7. Source: PubMed website viewed on Jan 22th, 2008 at 6:30 pm.

http://www.ncbi.nlm.nih.gov/pubmed/17017381?ordinalpos=25&itool=EntrezSystem2.PEntrez.Pubmed.Pubmed_ResultsPanel.Pubmed_RVDocSum

Merck & Co. Inc. 2005. Merck Wins New Jersey VIOXX Product Liability Case. http://www.merck.com

Miesfeld, R. 2000. Applied Molecular Genetics. http://www.biochem.arizona.edu/classes/bioc471/pages/Lecture19/Lecture19.html

MITACS-a, 2006. Health Care Operations Research
http://www.chcm.ubc.ca/mitacs_home.cfm

MITACS-b, 2006. Health Care System Operations (Carter, Puterman, Queyranne)
http://www.chcm.ubc.ca/mitacs_research.cfm

Monsanto. 2006. Who benefit from GM crops? Jan 2006, Pages 6, 16, 20, 25
http://www.foei.org/publications/pdfs/gmcrops2006full.pdf

Nicholson, j. 2002, Using Bisimulation to Facilitate Decision-Making in Partially-Observable Systems.
http://www.cs.mu.oz.au/481/2005_projects/jeremymn.pdf

Northwest Resistance Against Genetic Engineering. 2005. What is genetic engineering?
http://www.nwrage.org/modules.php?op=modload&name=Sections&file=index&req=viewarticle&artid=5&page=1

Organic Consumers Association. 2005. Mothers for Natural Law.
http://www.safe-food.org/-issue/ge.html

J. -M. Wal, P. A. Hepburn, L. J. Lea and R. W. R. Crevel . July 2004. Post-market surveillance of GM foods: applicability and limitations of schemes used with pharmaceuticals and some non-GM novel foods. Regulatory Toxicology and Pharmacology: Volume 38, Issue 1, August 2003, Pages 98-104
http://www.sciencedirect.com/science?_ob=ArticleURL&_udi=B6WPT-490H0TF-F&_user=10&_rdoc=1&_fmt=&_orig=search&_sort=d&view=c&_acct=C000050221&_version=1&_urlVersion=0&_userid=10&md5=40e9b9b3a73f1cfd0cc06e7001e36a3e

Public Health Agency of Canada, 2002. What Determines Health?. Viewed on April 18th, 2008 at 4:30 pm.
http://www.phac-aspc.gc.ca/ph-sp/phdd/determinants/determinants2.html

Public Health Agency of Canada. 2004. Global Public Health Intelligence Network (GPHIN)
http://www.phac-aspc.gc.ca/media/nr-rp/2004/2004_gphin-rmispbk_e.html#1

Prescott, L.M. 2007. The Role of Microorganisms in Genetic Engineering
http://www.microbiologybytes.com/introduction/GeneticEngineering.html

PSRAST, 2001. What is Genetic Engineering?
http://www.psrast.org/whatisge.htm

Russian Ministry of Health. 2002. Center of Sanitary and Epidemiological Standardization, Dec 2002
http://www.bisnis.doc.gov/bisnis/bisdoc/021219gmf-cert.htm

Rediscovery Biology. 2004. Genetically Modified Organisms, Unit 13,
http://www.learner.org/channel/courses/biology/textbook/gmo/gmo_7.html

Skinner, B. Rovere, M. 2007. Paying More, Getting Less 2007, Viewed on April 30th, 2008 at 10:12 pm.
http://www.fraserinstitute.org/COMMERCE.WEB/product_files/PayingMoreGettingLess2007.pdf

Starky, S. 2005. The Obesity epidemic in Canada, Library of Parliament, July 2005
http://www.parl.gc.ca/information/library/PRBpubs/prb0511-e.htm

Shah, A. 2001. Genetically Engineered Food.

http://www.betterhealth.vic.gov.au/bhcv2/bhcarticles.nsf/pages/Genetically_modified_foods_techniq ues

Silbergeld, M. 2005. Food Sensitivity.
http://pewagbiotech.org/buzz/display.php3?StoryID=13

StarLink, 2001. StarLink History, STARLINK LOGISTICS INC.
http://www.StarLinkcorn.com/History/What%20is%20StarLink%20corn.htm

Statistics Canada. 1996. Cancer Death.
http://www.statcan.ca/english/freepub/82-221-XIE/tables/pdftables/c1t12.pdf

Statistics Canada. 2000. Health Indicators, Dec 2000
http://www.statcan.ca/english/freepub/82-221-XIE/overview.htm

Statistics Canada. 2002. Comparable health indicators. Viewed on Jan 29 at 12:30 pm.
http://www.statcan.ca/Daily/English/021001/d021001c.htm

Statistics Canada. 2004a. Concepts, methods and data quality,
http://www.statcan.ca/english/research/82-620-MIE/2006002/concepts.htm#appendA

Statistics Canada. 2004b. Highlights.
http://www.statcan.ca/english/research/82-620-MIE/2006002/high.htm

Statistics Canada. 2004c. Overview of Canadians' Eating Habits.
http://www.statcan.ca/english/research/82-620-MIE/2006002/findings.htm#concluding

Statistics Canada. 2005a. Data tables from the Canadian Community Health Survey (CCHS),
http://www.statcan.ca/english/research/82-620-MIE/2005001/tables.htm

Statistics Canada. 2005b. Obesity among children and adults.
http://www.statcan.ca/Daily/English/050706/d050706a.htm

Statistics Canada. 2006. Food consumption highlights.
http://www.statcan.ca/english/ads/23F0001XCB/highlight.htm#1

Statistics Canada. 2006b. Food Statistics.
http://www.statcan.ca/english/freepub/21-020-XIE/2005002/part1.htm

Statistics Canada, Sept 2007. Measures of health. Viewed on Jan 29th, at 11:10 AM
http://cansim2.statcan.ca/cgi-win/cnsmcgi.pgm?Lang=E&SP_Action=Result&SP_ID=2979&SP_TYP=4&SP_Sort=1

Statistics Canada, 2007b. Canadian Community Health Survey (CCHS) Viewed on April 12th, 2008 at 6:30 pm.

http://www.statcan.ca/cgi-bin/imdb/p2SV.pl?Function=getSurvey&SDDS=3226&lang=en&db=imdb&dbg=f&adm=8&dis=2

Tufts Center for the Study of Drug Development. 2005

http://csdd.tufts.edu/NewsEvents/NewsArticle.asp?newsid=58

U.S. federal government. 2004. Vioxx,

http://www.vioxx.com

Union of Concerned Scientists. 2005.

http://www.ucsU.S..org/food_and_environment/genetic_engineering/genetic-engineering-techniques.html

U.S. Food and Drug Administration. 2005. Genetically modified foods techniques,

http://www.fda.gov/cder/drug/infopage/vioxx/vioxxQA.htm

Vioxx News. 2005. FDA whistleblower creates more waves regarding Vioxx, January 26, 2005

http://www.vioxxlawsuithelp.com/html/fda-whistleblower.html

Washington State University, 2006, Demand for a Segregation System for U.S. Wheat is on the Rise, 2006

http://impact.typepad.com/articles/2006/01/index.html

Williams, J. Young, S. 2006. Partially observable Markov decision processes for spoken dialog systems.

http://mi.eng.cam.ac.uk/~sjy/papers/wiyo07.pdf

Weisser K, Meyer C, Petzold D, Mentzer D, Keller-Stanislawski B., Nov 2007. Adverse drug reactions following immunization in Germany pursuant to the German Infection Protection Act and the German Medicinal Products Act from January 1, 2004 to December 31, 2005, 50(11):1404-17. Source: PubMed website viewed on Jan 20th, 2008 at 6:30 pm.

http://www.ncbi.nlm.nih.gov/pubmed/17999134?ordinalpos=1&itool=EntrezSystem2.PEntrez.Pubmed.Pubmed_ResultsPanel.Pubmed_RVDocSum

WHO, October 2005. Guidance on public health measures in countries experiencing their first outbreaks of H5N1 avian influenza. Source viewed on Jan 28th at 7:00 pm.
http://www.who.int/csr/disease/avian_influenza/guidelines/firstoutbreak/en/index.html

Zhuo Q, Yang XG, Wei Sheng Yan Jiu, March 2005. Strategies for safety assessment of genetically modified crops: current and future development. Source: PubMed website viewed on Jan 28th, 2008 at 9:45 pm.

http://www.ncbi.nlm.nih.gov/pubmed/15952675?ordinalpos=20&itool=EntrezSystem2.PEntrez.Pubmed.Pubmed_ResultsPanel.Pubmed_RVDocSum

APPENDIX A:
Surveillance of Obesity as an Example

Appendix A demonstrates the application of obesity, in a specific health population. As a base case, first the model illustrates the effect of monthly transition of obesity-related health status over a year without any intervention or policy adjustment. Then the same data are used with other possible interventions based on different policy alarm levels. Four different Experiments are used to observe the effect of different policy interventions and alarms on health status. These Experiments are: No-alarm, Low-alarm, Moderate-alarm, and Extensive-alarm.

A. Model Illustration in Case of Obesity

The following section illustrates an example of an obesity model in four different cases: when there is No-alarm, when there are Low-alarms, when there are Moderate-alarms, or when there are Extensive-alarms implemented into the simulation model.

A.1 Alarms

There are three type of alarms used in this model:

Alarms Types

Type 0	Type 1	Type 2	Type 3
Alarm 0	Alarm 1	Alarm 2	Alarm 3
No-alarm	Low-alarm	Moderate-alarm	Extensive-alarm

Table A1: Different alarms type

Each alarm has its own condition to trigger its intervention for improvement of the system. The conditions and intervention levels are shown in following:

Alarm's Type:	Alarm off: Type 0	Alarm On: Type 1	Alarm On: Type 2	Alarm On: Type 3
Conditions:	If (S5 <= 0.05)	If (0.05 < S5 < 0.2)	If (S5 > = 0.2)	If Alarm 2 has been repeated in last two time periods
Interventions:	No intervention	10% intervention	25% intervention	40% intervention

Table A2: Different alarms type and their interventions' percentages

Interventions denote the change in the seasonal transition probability matrices.

A.2 Cost Related Vector

Cost is an important factor for any decision-making method. The model demonstrated in this research, offers different scenarios and methods. Each method has its own cost attached to it. Based on data estimated from Health Canada statistics, the cost related to each health status is estimated and applied to evaluate the periodic cost impacts of each intervention. The population for this estimation is based on the latest Statistics Canada data, where Canada's population was estimated to be 33,098,932 in July 2006 (CIA, 2007).

The Fraser institute forecasted that heath care spending in Canada for 2006 was $148 billion or $4548 per person per year. In this model, the cost of obesity has been assumed as a base case of simply $2000 per person per year. Therefore the obesity case health-related cost estimates are as follows:

Health Care Cost (Obesity related) / person/Year:	$2000 (Assumption based on $4548/person/year)
Health Care Cost (Obesity related) / Population/Year:	$2000 x 33,098,932 = $66,197,864,000
Health Care Cost (Obesity related) / population (33,098,932)/month:	$66,197,864,000 ÷ 12 = $5,516,488,667

Based on this estimate, the monthly obesity health cost is estimated at $5,516,488,667. Table A3 shows how the health costs are attributed to each health care state. The scale is based on the obesity health care cost (HCC) per total population per month:

	HCC/Pop/m	Assumed Portions /Scale	Round value per Million
Fit & healthy	$5,516,488,667	0.25	$1,379
Average	$5,516,488,667	0.55	$3,034
Heavy	$5,516,488,667	1	$5,516
Overweight	$5,516,488,667	2	$11,033
Obese	$5,516,488,667	4	$22,066

Table A3: the scale of the obesity health care cost (HCC) per total population per month

Therefore the estimated cost is defined in a vector (Table A4) as follows:

S1	S2	S3	S4	S5
Fit & Healthy	Average	Heavy	Overweight	Obese
$1,379	$3,034	$5,516	$11,033	$22,066

Table A4: Obesity and its health costs estimates

A.3 State Seasonality Transition Matrices

Four single period (monthly) period-over-period probability transition matrices are used to simulate the effect of each season's monthly changes on the health status states of a population. There are four seasons in the year: Fall, Winter, Spring, and Summer, each with a 3 month duration. All probability transition matrices are stochastic matrices, i.e., their rows sum to one, and each cell {ij} of the matrices represent the probability that State i moves to State j in the course of one month. The following sections show seasonality transition matrices.

A.3.1 Fall Transition Matrix

	Fit & Healthy	Average	Heavy	Overweight	Obese	Total
Fit & Healthy	0.45	0.3	0.15	0.075	0.025	1
Average	0.2	0.45	0.2	0.1	0.05	1
Heavy	0.1	0.15	0.45	0.2	0.1	1
Overweight	0.05	0.05	0.15	0.45	0.3	1
Obese	0.025	0.075	0.15	0.25	0.5	1

Table A5: Fall transition matrix

A.3.2 Winter Transition Matrix

	Fit & Healthy	Average	Heavy	Overweight	Obese	Total
Fit & Healthy	0.2	0.3	0.3	0.15	0.05	1
Average	0.15	0.2	0.15	0.2	0.3	1
Heavy	0.01	0.05	0.09	0.45	0.4	1
Overweight	0.02	0.02	0.06	0.4	0.5	1
Obese	0.01	0.01	0.01	0.27	0.7	1

Table A6: Winter transition matrix

A.3.3 Spring Transition Matrix

	Fit & Healthy	Average	Heavy	Overweight	Obese	Total
Fit & Healthy	0.27	0.22	0.15	0.16	0.2	1
Average	0.2	0.2	0.2	0.15	0.25	1
Heavy	0.1	0.15	0.3	0.2	0.25	1
Overweight	0.05	0.05	0.15	0.4	0.35	1
Obese	0.02	0.03	0.1	0.25	0.6	1

Table A7: Spring transition matrix

A.3.4 Summer Transition Matrix

	Fit & Healthy	Average	Heavy	Overweight	Obese	Total
Fit & Healthy	0.6	0.35	0.03	0.01	0.01	1
Average	0.5	0.4	0.06	0.02	0.02	1
Heavy	0.2	0.35	0.15	0.08	0.22	1
Overweight	0.1	0.25	0.15	0.2	0.3	1
Obese	0.05	0.23	0.1	0.22	0.4	1

Table A8: Summer transition matrix

A.4 Transition Response Matrices:

A probability transition matrix is a key element to respond to an alarm type. When an alarm is on, depending on its level, the corresponding transition matrix responds. Therefore, for each type of alarm there is a specific type of probability transition matrix. These transition matrices are subjected to change with each season. As a result, each season has its own different transition matrices where it changes through alarm response. For instance, if the low level alarm is on, the original transition matrix will switch to low level (10%) transition matrix. In the case of the moderate level alarm, it will switch to moderate level (25%) transition matrix and in the case of high level alarm, it will switch to high level (40%) transition matrix. The 10%, 25% or 40% represent the approximate percentage of change of an original probability transition matrix in the corresponding season.

A.4.1 No-Alarm Transition Matrix

The following fall probability transition matrix (table 96) is shown as an example of a No-alarm case matrix. See table 96.

	Fit & Healthy	Average	Heavy	Overweight	Obese	Total
Fit & Healthy	0.45	0.3	0.15	0.075	0.025	1
Average	0.2	0.45	0.2	0.1	0.05	1
Heavy	0.1	0.15	0.45	0.2	0.1	1
Overweight	0.05	0.05	0.15	0.45	0.3	1
Obese	0.025	0.075	0.15	0.25	0.5	1

Table A9: The No-alarm case transition matrix

A.4.2 Low-Alarm Transition Matrix

The same sample of the fall season is used to demonstrate a Low-alarm probability matrix with approximate 10% changes to table 96 improve health status as a response to a low policy intervention. See table 97.

	Fit & Healthy	Average	Heavy	Overweight	Obese	Total
Fit & Healthy	0.44	0.33	0.2	0.02	0.01	1
Average	0.22	0.44	0.22	0.07	0.05	1
Heavy	0.11	0.22	0.44	0.15	0.08	1
Overweight	0.06	0.11	0.22	0.36	0.25	1
Obese	0.03	0.1	0.16	0.35	0.36	1

Table A10: Alarm (1) with 10% intervention

A.4.3 Moderated-Alarm Transition Matrix

The same fall example is again used to demonstrate a Moderate-alarm probability matrix with approximate 25% changes to table 96 to improve health status as a response to a moderate policy intervention. See table 98

	Fit & Healthy	Average	Heavy	Overweight	Obese	Total
Fit & Healthy	0.56	0.27	0.13	0.03	0.01	1
Average	0.27	0.5	0.13	0.06	0.04	1
Heavy	0.15	0.3	0.29	0.16	0.1	1
Overweight	0.1	0.15	0.3	0.2	0.25	1
Obese	0.08	0.1	0.15	0.25	0.42	1

Table A11: Alarm (2) with 25% intervention

A.4.4 Extensive-Alarm Transition Matrix

The same fall example is used to demonstrate an Extensive-alarm probability matrix with approximate 40% changes to table 96 to improve health status as a response to an extensive policy intervention. See table 99.

	Fit & Healthy	Average	Heavy	Overweight	Obese	Total
Fit & Healthy	0.65	0.25	0.06	0.03	0.01	1
Average	0.35	0.51	0.1	0.01	0.03	1
Heavy	0.2	0.2	0.34	0.13	0.13	1
Overweight	0.15	0.18	0.2	0.22	0.25	1
Obese	0.1	0.15	0.13	0.25	0.37	1

Table A12: Alarm (3) with 40% intervention

A.5 Reliability Matrix

The reliability matrix provides probability distributions for describing the observations about health status that may occur, assuming that the population is in fact in a particular health status. Let reliability matrix R, represent the reliability of the state-to-observation probabilities (Table 100) for the obesity case study.

		Observation				
		O1	**O2**	**O3**	**O4**	**O5**
States	**Fit & Healthy**	0.4	0.3	0.15	0.1	0.05
	Average	0.3	0.3	0.2	0.1	0.1
	Heavy	0.1	0.2	0.4	0.2	0.1
	Overweight	0.07	0.1	0.28	0.3	0.25
	Obese	0.03	0.1	0.17	0.3	0.4

Table A13: Reliability matrix (State to Observation matrix)

A.6 Model Experiment

In the previous section the obesity model, its states and transition and observation matrices were defined. This section will demonstrate the experimental obesity model.

A.6.1 Initial State:

The initial state is based on the health status of a sample population. The population is divided into health status groups. These groups describe the percentages of the population grouped into five different health status: (1) fit & healthy, (2) average, (3) heavy, (4) overweight, and (5) obese. The highest health condition (State 1) applies to very fit & healthy groups of people, while the obese condition (State 5) applies to those with the worst case health status. Assume that the initial state of the entire population is in State 1, the fit & healthy condition. Therefore, the initial health status vector is denoted by the initial state vector: $\{1, 0, 0, 0, 0\}$. See table 101.

Initial state:	1

Table A14: Initial state

A.6.2 Initial Period-Over-Period Transition

The next state in the time chain is simulated by using the state–to-state transition matrix and a (0,1) random number generator to determine the next state. Assuming the following period-to-period transition matrix (5x5) of Table 102:

	Fit & Healthy	Average	Heavy	Overweight	Obese
Fit & Healthy	0.45	0.3	0.15	0.075	0.025
Average	0.2	0.45	0.2	0.1	0.05
Heavy	0.1	0.15	0.45	0.2	0.1
Overweight	0.05	0.05	0.15	0.45	0.3
Obese	0.025	0.075	0.15	0.25	0.5

Table A15: A fall state transition matrix

The accumulated state probability can be calculated based on the above matrix and the cell-by-cell sums of the row-wise probabilities (Table 103):

		S1	S1+S2	S1+S2+S3	S1+S2+S3+S4
Fit & Healthy	0	0.45	0.75	0.9	0.975
Average	0	0.2	0.65	0.85	0.95
Heavy	0	0.1	0.25	0.7	0.9
Overweight	0	0.05	0.1	0.25	0.7
Obese	0	0.025	0.1	0.25	0.5

Table A16: An accumulation of fall state probability matrix

A.6.3 Next State

The next actual state of the population can be randomly generated based on the accumulated probability matrix (Table 103). The random generation of a number between 0 and 1 is directly comparable to the outcomes in the first row of the matrix that represent a state movement over one period (a month) from health status 1, to states 1 to 5 of this accumulated probability matrix. Since, the initial state was State 1, than the random generator value will be compared to the first row of the accumulated probability matrix. For example, if the random generator provides a number between 0.45 and 0.75, then the next state will be State 2 (the second column of the matrix).

Initial state:	2

Table A17: The next state

Therefore, the second period health status vector is denoted by the state vector: $\{0, 1, 0, 0, 0\}$.

A.6.4 State-to-Observation Matrix

The health status of the population, under surveillance, produces observations that are a function of the actual state. Moreover, the probability over the observation outcomes space for each actual state can be described in the state-to-observation matrix, also known as the "reliability matrix". For this case, the observation matrix is presented in Table 105 with possible outcomes denoted as Oj, j=1,2,3,4,5:

		Observation				
		O1	O2	O3	O4	O5
States	Fit & Healthy	0.4	0.3	0.15	0.1	0.05
	Average	0.3	0.3	0.2	0.1	0.1
	Heavy	0.1	0.2	0.4	0.2	0.1
	Overweight	0.07	0.1	0.28	0.3	0.25
	Obese	0.03	0.1	0.17	0.3	0.4

Table A18 An observation matrix in model

The accumulated state-to-observation probability matrix can be calculated based on the above matrix. Each cell of state transition in above in a row is added to the next cell at the same row and the result is recorded in this following table (Table106):

		Accumulated State-to-Observation Probability Matrix				
		O1	O2	O3	O4	O5
States	Fit & Healthy	0	0.4	0.7	0.85	0.95
	Average	0	0.3	0.6	0.8	0.9
	Heavy	0	0.1	0.3	0.7	0.9
	Overweight	0	0.07	0.17	0.45	0.75
	Obese	0	0.03	0.13	0.3	0.6

Table A19: An accumulation state probability matrix in model

Since the actual previous state was determined to be state 2, the observation will be chosen randomly from row two of Table 105. If a generated random number for example is between 0.8 and 0.9, the generated observation, O(1) value will be O4:

Observation (O(1)):	**4**

Table A20: The first generated observation state

Similarly, the initial state vector can be assumed to be a vector with non-zero estimates for all 5 states, representing the (1) fit & healthy, (2) average, (3) heavy, (4) overweight and (5) obese state:

Initial state vector

Si(t) =

S1	S2	S3	S4	S5
0.2	0.4	0.2	0.15	0.05

Table A21: An initial state vector

The updated new state vector estimation can be determined based on the assumed initial state, the state transition matrix, and the observation value using Bayes Theorem. First, multiply the initial by the fall period-over-period transition matrices:

Initial state vector

Si(t) =

S1	S2	S3	S4	S5
0.2	0.4	0.2	0.15	0.05

X

State to State Transition Matrix

	S1	S2	S3	S4	S5
S1	0.45	0.3	0.15	0.075	0.025
S2	0.2	0.45	0.2	0.1	0.05
S3	0.1	0.15	0.45	0.2	0.1
S4	0.05	0.05	0.15	0.45	0.3
S5	0.025	0.075	0.15	0.25	0.5

Table A22: The initial state and the fall transition matrix are multiplied

The result will be the updated next state vector:

Next state vector

	S1	S2	S3	S4	S5
Si'(t) =	0.18875	0.27875	0.2575	0.1725	0.1025

Table A23: The next state vector

The last observation was:

Observation (O(1)):	4

Table A24: The last observation state

Therefore, the new state matrix, Si'(t), will be multiplied with the 4th column of the observation matrix:

		Observation				
		O1	O2	O3	O4	O5
States	Fit & Healthy	0.4	0.3	0.15	**0.1**	0.05
	Average	0.3	0.3	0.2	**0.1**	0.1
	Heavy	0.1	0.2	0.4	**0.2**	0.1
	Overweight	0.07	0.1	0.28	**0.3**	0.25
	Obese	0.03	0.1	0.17	**0.3**	0.4

Table A25: The new state multiplies with the 4th column of observation matrix

The result will be:

State Vector

	S1	S2	S3	S4	S5
Si'(t) =	0.18875	0.2788	0.2575	0.1725	0.1025

X

O4
0.1
0.1
0.2
0.3
0.3

=

Product
0.018875
0.027875
0.0515
0.05175
0.03075
sum: **0.18075**

Table A26: The product of two matrices

The sum of the entries in Table 113 is: 0.18075. Next, every cell of the vector will be divided by 0.18075. This yields the new state vector probability estimate:

	Next State				
	S1	**S2**	**S3**	**S4**	**S5**
Sj(t) =	0.104426	0.15421853	0.284923928	0.286307054	**0.170124481**

Table A27: The final state with its S5 value

The S1 estimate represents the excellent, fit & healthy condition of the population. S5, on the other hand, represents the worst case, the obese condition. Since the objective of this analysis is to improve the worst case results, it is desirable to focus on the worst case outcome, S5, an important element of this vector. S5 estimates are used to trigger remedial action including system alarms and interventions.

To find the next vector state with intervention (alarm), the new procedures are followed. The updated state is now (see table 105 above).

Since S5 is greater than 0.05 and less than 0.2, the type (1) alarm is triggered for action in the next period.

Alarm rate:
1

Table A28: The alarm rate

The observation matrix (table 106) is time-invariant and remains the same for each period. Changes in the period-over-period transition matrix occur in each season. Since the alarm type is 1, the next state will be randomly selected, using the Alarm 1 state transition matrix. The different alarm matrices were demonstrated in last section. The Alarm 1 Probability State Transition matrix (table 97) is:

	Fit & Healthy	Average	Heavy	Overweight	Obese	Total
Fit & Healthy	0.44	0.33	0.2	0.02	0.01	1
Average	0.22	0.44	0.22	0.07	0.05	1
Heavy	0.11	0.22	0.44	0.15	0.08	1
Overweight	0.06	0.11	0.22	0.36	0.25	1
Obese	0.03	0.1	0.16	0.35	0.36	1

Table A29: The Alarm 1 state transition matrix

The accumulated state probability of the alarm (1) matrix can be calculated based on the above matrix. The result is recorded in this following matrix:

			S1	S1+S2	S1+S2+S3	S1+S2+S3+S4
		Fit & Healthy	Average	Heavy	Overweight	Obese
S1	Fit & Healthy	0	0.44	0.77	0.97	0.99
S2	Average	0	0.22	0.66	0.88	0.95
S3	Heavy	0	0.11	0.33	0.77	0.92
S4	Overweight	0	0.06	0.17	0.39	0.75
S5	Obese	0	0.03	0.13	0.29	0.64

Table A30: The accumulated state probability of the alarm (1)

Using the above matrix and the random number generator, the next state will be:

New state:	3

Table A31: The next state

Now using the observation matrix, the next observation will be determined:

Observation (O(2)):	**5**

Table A32: The next observation

Also as we had before, the alarm rate was Type (1) and the state was 3. Therefore, by following the same procedure using the last state vector, Sj(t) and using the alarm(1) State transition matrix, the next state vector Sk(t) will be determined:

Next State Vector

	S1	**S2**	**S3**	**S4**	**S5**
Sk(t) =	0.03	0.107	0.127	0.321	**0.416**

Table A33: The next state vector

After this stage where the next state vector is determined, the next step is to find the type of associated alarm which can be triggered with S5 state. The next section describes a procedure where the final alarm is associated to old and new triggered alarms.

A.7 Experiment I: No-Alarm (No-Policy Intervention) for First Two Months

The No-policy intervention model demonstrates a model with no plan to intervene and without any implementation of new policy. Therefore, there is no need for an alarm system. The model follows a seasonality change through a transition matrix, during one year period trial. There are ten independent trials for this model. In this appendix, only two months of the one trial are demonstrated.

Update # 1: No-Alarm Season: Fall (October)

Initial state: 1

Fit & healthy	Average	Heavy	Overweight	Obese
1	2	3	4	5
$1,379	$3,034	$5,516	$11,033	$22,066

Table A: State to state transition matrix

	Fit & healthy	Average	Heavy	Overweight	Obese	Total
Fit & healthy	0.45	0.3	0.15	0.075	0.025	1
Average	0.2	0.45	0.2	0.1	0.05	1
Heavy	0.1	0.15	0.45	0.2	0.1	1
Overweight	0.05	0.05	0.15	0.45	0.3	1
Obese	0.025	0.075	0.15	0.25	0.5	1

Table B: Accumulated state probs

	Fit & healthy	Average	Heavy	Overweight	Obese
Fit & healthy	0	0.45	0.75	0.9	0.975
Average	0	0.2	0.65	0.85	0.95
Heavy	0	0.1	0.25	0.7	0.9
Overweight	0	0.05	0.1	0.25	0.7
Obese	0	0.025	0.1	0.25	0.5
	1	2	3	4	5

New state: 1

Table C: State to observation matrix

	O1	O2	O3	O4	O5
Fit & healthy	0.4	0.3	0.15	0.1	0.05
Average	0.3	0.3	0.2	0.1	0.1
Heavy	0.1	0.2	0.4	0.2	0.1
Overweight	0.07	0.1	0.28	0.3	0.25
Obese	0.03	0.1	0.17	0.3	0.4

Table D: Accumulated state probs

Fit & healthy	0	0.4	0.7	0.85	0.95	1
Average	0	0.3	0.6	0.8	0.9	1
Heavy	0	0.1	0.3	0.7	0.9	1
Overweight	0	0.07	0.17	0.45	0.75	1
Obese	0	0.03	0.13	0.3	0.6	1
	1	2	3	4	5	

Observation (O1): 3

{ Initial state vector based on assumption}

	S1	S2	S3	S4	S5		
Si(t) = [	0.2	0.4	0.2	0.15	0.05	]	X

	Fit & healthy	Average	Heavy	Overweight	Obese	Total	Fall
Fit & healthy	0.45	0.3	0.15	0.075	0.025	1	
Average	0.2	0.45	0.2	0.1	0.05	1	
Heavy	0.1	0.15	0.45	0.2	0.1	1	
Overweight	0.05	0.05	0.15	0.45	0.3	1	
Obese	0.025	0.075	0.15	0.25	0.5	1	

Si'(t) = [	0.20	0.28	0.23	0.18	0.12	]	X

	O1	O2	O3	O4	O5	Total			
Fit & healthy	0.40	0.30	0.15	0.10	0.05	1.00	0.03	O/sum =	0.12
Average	0.30	0.30	0.20	0.10	0.10	1.00	0.06	O/sum =	0.23
Heavy	0.10	0.20	0.40	0.20	0.10	1.00	0.09	O/sum =	0.37
Overweight	0.07	0.10	0.28	0.30	0.25	1.00	0.05	O/sum =	0.20
Obese	0.03	0.10	0.17	0.30	0.40	1.00	0.02	O/sum =	0.08
						Sum =	0.25		
									1.00

Alarm rate: (no possibility of alarm)

0

Total Alarm 1	Total Alarm 2	Total Alarm 3
0	0	0

New State	S1	S2	S3	S4	S5		
Sj(t) = [	0.12	0.23	0.37	0.20	0.08	]	
Cost:	$314.54	$692.03	$2,057.77	$2,192.17	$1,749.26	$7,005.77	

Figure A1: Demonstration of Experiment I: No-alarm Intervention for the update in October

Update # 2: **Season: Fall (November)** **Total cost so far: $7,005.77**

Previous state: 1

Alarm-off Table A: state transition matrix

	Fit & healthy	Average	Heavy	Overweight	Obese	Total
Fit & healthy	**0.45**	**0.3**	**0.15**	**0.075**	**0.025**	1
Average	**0.2**	**0.45**	**0.2**	**0.1**	**0.05**	1
Heavy	**0.1**	**0.15**	**0.45**	**0.2**	**0.1**	1
Overweight	**0.05**	**0.05**	**0.15**	**0.45**	**0.3**	1
Obese	**0.025**	**0.075**	**0.15**	**0.25**	**0.5**	1

Table B: mulated state probs

	Fit & healthy	Average	Heavy	Overweight	Obese
Fit & healthy	0	0.45	0.75	0.9	0.975
Average	0	0.2	0.65	0.85	0.95
Heavy	0	0.1	0.25	0.7	0.9
Overweight	0	0.05	0.1	0.25	0.7
Obese	0	0.025	0.1	0.25	0.5
rate	**1**	**2**	**3**	**4**	**5**

Conditional new state:

Alarm: 0	**3**
Alarm: 1	**1**
Alarm: 2	**3**
Alarm: 3	**1**

Previous Alarm: **0**

Therefore:

Final new state: **3**

Table C: State to observation matrix

	O1	O2	O3	O4	O5
Fit & healthy	0.4	0.3	0.15	0.1	0.05
Average	0.3	0.3	0.2	0.1	0.1
Heavy	0.1	0.2	0.4	0.2	0.1
Overweight	0.07	0.1	0.28	0.3	0.25
Obese	0.03	0.1	0.17	0.3	0.4

Table D: Accumulated state probs

	O1	O2	O3	O4	O5
Fit & healthy	0	0.4	0.7	0.85	0.95
Average	0	0.3	0.6	0.8	0.9
Heavy	0	0.1	0.3	0.7	0.9
Overweight	0	0.07	0.17	0.45	0.75
Obese	0	0.03	0.13	0.3	0.6
rate	**1**	**2**	**3**	**4**	**5**

Observation (O2): **2**

	S1	S2	S3	S4	S5
Sj(t) = [	**0.12**	**0.23**	**0.37**	**0.20**	**0.08**] X

Alarm-off

	Fit & healthy	Average	Heavy	Overweight	Obese	Total
Fit & healthy	**0.45**	**0.3**	**0.15**	**0.075**	**0.025**	1
Average	**0.2**	**0.45**	**0.2**	**0.1**	**0.05**	1
Heavy	**0.1**	**0.15**	**0.45**	**0.2**	**0.1**	1
Overweight	**0.05**	**0.05**	**0.15**	**0.45**	**0.3**	1
Obese	***0.025***	***0.075***	***0.15***	***0.25***	***0.5***	1

Sj'(t) = [**0.15** **0.21** **0.27** **0.22** **0.15**] X

	O1	O2	O3	O4	O5	Total			
Fit & healthy	**0.40**	**0.30**	**0.15**	**0.10**	**0.05**	1	**0.04**	O/sum =	**0.22**
Average	**0.30**	**0.30**	**0.20**	**0.10**	**0.10**	1	**0.06**	O/sum =	**0.32**
Heavy	**0.10**	**0.20**	**0.40**	**0.20**	**0.10**	1	**0.05**	O/sum =	**0.27**
Overweight	**0.07**	**0.10**	**0.28**	**0.30**	**0.25**	1	**0.02**	O/sum =	**0.11**
Obese	**0.03**	**0.10**	**0.17**	**0.30**	**0.40**	1	**0.02**	O/sum =	**0.08**
						Sum	**0.20**		

Sk(t) = [**0.22** **0.32** **0.27** **0.11** **0.08**]

New-Alarm	Pre-Alarm	Final Alarm	Total Alarm 1	Total Alarm 2	Total Alarm 3
0	0	0	0	0	0

Cost: $309.74 $962.33 $1,512.71 $1,194.01 $1,671.34 **sum:** 5650.126187

Update # 3: **Season: Fall (December)** **Total cost so far: $12,655.90**

Figure A2: Demonstration of Experiment I: No-alarm Intervention for the update in November

A.8 Experiment II: Low-Alarm (Low-Policy Intervention) for First Two Months

The Low-policy intervention model demonstrates a model with a smooth implementation policy. Therefore, the applied policy depends on the level of the alarm system. S5, which represents obesity in a health states vector, is assigned to an alarm. The alarm's sensitivity is set to a range of 0.1 to 0.3 for the S5 value. The model follows a seasonality change through a transition matrix, during a one year period trial. There are ten independent trials for this model. In this appendix, only two months of one trial are demonstrated.

Update # 1: **Low Alarm** **Season:** **Fall (October)**

Initial state:	**1**

Table A: State to state transition matrix

	Fit & healthy	Average	Heavy	Overweight	Obese	Total
Fit & healthy	**0.45**	**0.3**	**0.15**	**0.075**	**0.025**	1
Average	**0.2**	**0.45**	**0.2**	**0.1**	**0.05**	1
Heavy	**0.1**	**0.15**	**0.45**	**0.2**	**0.1**	1
Overweight	**0.05**	**0.05**	**0.15**	**0.45**	**0.3**	1
Obese	**0.025**	**0.075**	**0.15**	**0.25**	**0.5**	1

Table B: Accumulated state probs

	AA				AE
1	0	0.45	0.75	0.9	0.975
2	0	0.2	0.65	0.85	0.95
3	0	0.1	0.25	0.7	0.9
4	0	0.05	0.1	0.25	0.7
5	0	0.025	0.1	0.25	0.5
rate	1	2	3	4	5

New state:	**1**

Table C: State to observation matrix

	O1	O2	O3	O4	O5
Fit & healthy	0.4	0.3	0.15	0.1	0.05
Average	0.3	0.3	0.2	0.1	0.1
Heavy	0.1	0.2	0.4	0.2	0.1
Overweight	0.07	0.1	0.28	0.3	0.25
Obese	0.03	0.1	0.17	0.3	0.4

Table D: Accumulated state probs

1	0	0.4	0.7	0.85	0.95
2	0	0.3	0.6	0.8	0.9
3	0	0.1	0.3	0.7	0.9
4	0	0.07	0.17	0.45	0.75
5	0	0.03	0.13	0.3	0.6
rate	1	2	3	4	5

bservation (O1):	**5**

Fall

{ Initial state vector based on assumption}

	S1	S2	S3	S4	S5	
Si(t) = [	0.2	0.4	0.2	0.15	0.05	] X

	1	2	3	4	5	Total
1	0.4	0.3	0.2	0.075	0.025	1
2	0.2	0.4	0.25	0.1	0.05	1
3	0.1	0.2	0.4	0.2	0.1	1
4	0.05	0.1	0.2	0.4	0.25	1
5	0.025	0.075	0.15	0.35	0.4	1

Si'(t) = [	0.19	0.28	0.26	0.17	0.10	] X

	O1	O2	O3	O4	O5	Total			
1	0.4	0.3	0.15	0.1	0.05	1	0.01	O/sum =	0.06
2	0.3	0.3	0.2	0.1	0.1	1	0.03	O/sum =	0.19
3	0.1	0.2	0.4	0.2	0.1	1	0.03	O/sum =	0.17
4	0.07	0.1	0.28	0.3	0.25	1	0.04	O/sum =	0.29
5	0.03	0.1	0.17	0.3	0.4	1	0.04	O/sum =	0.28
						Sum =	0.15		

New State

					S5		
Sj(t) = [	$0.06	$0.19	$0.17	$0.29	$0.28	]	
	$88.42	$574.59	$965.01	$3,232.60	$6,146.62		$11,007.24

Alarm rate:	(no possibility of alarm 3)
1	

Total Alarm 1	Total Alarm 2	Total Alarm 3
1	0	0

Figure A3: Demonstration of Experiment II: Low-alarm Intervention for the update in October

Update # 2: **Season: Fall (November)** **$11,007.24**

Initial state:	1

Table A: State to state transition matrix

	Fit & healthy	Average	Heavy	Overweight	Obese	Total
Fit & healthy	0.45	0.3	0.15	0.075	0.025	1
Average	0.2	0.45	0.2	0.1	0.05	1
Heavy	0.1	0.15	0.45	0.2	0.1	1
Overweight	0.05	0.05	0.15	0.45	0.3	1
Obese	0.025	0.075	0.15	0.25	0.5	1

Table B: Accumulated state probs

	AA				AE
1	0	0.45	0.75	0.9	0.975
2	0	0.2	0.65	0.85	0.95
3	0	0.1	0.25	0.7	0.9
4	0	0.05	0.1	0.25	0.7
5	0	0.025	0.1	0.25	0.5

Table A: State to state transition matrix

	Fit & healthy	Average	Heavy	Overweight	Obese	Total
Fit & healthy	**0.45**	**0.3**	**0.15**	**0.075**	**0.025**	1
Average	**0.2**	**0.45**	**0.2**	**0.1**	**0.05**	1
Heavy	**0.1**	**0.15**	**0.45**	**0.2**	**0.1**	1
Overweight	**0.05**	**0.05**	**0.15**	**0.45**	**0.3**	1
Obese	**0.025**	**0.075**	**0.15**	**0.25**	**0.5**	1

New state:	**1**

Table B: Accumulated state probs

1	0	0.45	0.75	0.9	0.975
2	0	0.2	0.65	0.85	0.95
3	0	0.1	0.25	0.7	0.9
4	0	0.05	0.1	0.25	0.7
5	0	0.025	0.1	0.25	0.5

Table C: State to observation matrix

	O1	O2	O3	O4	O5
Fit & healthy	0.4	0.3	0.15	0.1	0.05
Average	0.3	0.3	0.2	0.1	0.1
Heavy	0.1	0.2	0.4	0.2	0.1
Overweight	0.07	0.1	0.28	0.3	0.25
Obese	0.03	0.1	0.17	0.3	0.4

bservation (O1):	**5**

Table D: Accumulated state probs

1	0	0.4	0.7	0.85	0.95
2	0	0.3	0.6	0.8	0.9
3	0	0.1	0.3	0.7	0.9
4	0	0.07	0.17	0.45	0.75
5	0	0.03	0.13	0.3	0.6
rate	1	2	3	4	5

{ Initial state vector based on assumption}

	S1	S2	S3	S4	S5	
Si(t) = [	**0.2**	**0.4**	**0.2**	**0.15**	**0.05**	] X

	1	2	3	4	5	Total
1	**0.4**	**0.3**	**0.2**	**0.075**	**0.025**	1
2	**0.2**	**0.4**	**0.25**	**0.1**	**0.05**	1
3	**0.1**	**0.2**	**0.4**	**0.2**	**0.1**	1
4	**0.05**	**0.1**	**0.2**	**0.4**	**0.25**	1
5	**0.025**	**0.075**	**0.15**	**0.35**	**0.4**	1

	S1	S2	S3	S4	S5	
Si'(t) = [	**0.19**	**0.28**	**0.26**	**0.17**	**0.10**	] X

	O1	O2	O3	O4	O5	Total			
1	**0.4**	**0.3**	**0.15**	**0.1**	**0.05**	1	**0.01**	O/sum =	**0.06**
2	**0.3**	**0.3**	**0.2**	**0.1**	**0.1**	1	**0.03**	O/sum =	**0.19**
3	**0.1**	**0.2**	**0.4**	**0.2**	**0.1**	1	**0.03**	O/sum =	**0.17**
4	**0.07**	**0.1**	**0.28**	**0.3**	**0.25**	1	**0.04**	O/sum =	**0.29**
5	**0.03**	**0.1**	**0.17**	**0.3**	**0.4**	1	**0.04**	O/sum =	**0.28**
						Sum	**0.15**		

New State

					S5		
Sj(t) = [	**$0.06**	**$0.19**	**$0.17**	**$0.29**	**$0.28**	]	
	$88.42	$574.59	$965.01	$3,232.60	$6,146.62		**$11,007.24**

Alarm	(no possibility of alarm 3)
1	

Total Alarm 1	Total Alarm 2	Total Alarm 3
1	**0**	**0**

Figure A4: Demonstration of model Experiment II: Low-Policy Intervention in November

Update # 2: **Season: Fall (November)** **Cost so far:** **$11,007.24**

Previous Alarm: 1

Previous state: 1

Alarm-Type 1 Table A: State to state transition matrix

	Fit & healthy	Average	Heavy	Overweight	Obese	Total
Fit & healthy	**0.44**	**0.33**	**0.2**	**0.02**	**0.01**	1
Average	**0.22**	**0.44**	**0.22**	**0.07**	**0.05**	1
Heavy	**0.11**	**0.22**	**0.44**	**0.15**	**0.08**	1
Overweight	**0.06**	**0.11**	**0.22**	**0.36**	**0.25**	1
Obese	**0.03**	**0.1**	**0.16**	**0.35**	**0.36**	1

Table B: Accumulated state probs

1	**0**	**0.44**	**0.77**	**0.97**	**0.99**
2	**0**	**0.22**	**0.66**	**0.88**	**0.95**
3	**0**	**0.11**	**0.33**	**0.77**	**0.92**
4	**0**	**0.06**	**0.17**	**0.39**	**0.75**
5	**0**	**0.03**	**0.13**	**0.29**	**0.64**

Final new state: 2

Table C: State to observation matrix

	O1	O2	O3	O4	O5
Fit & healthy	0.4	0.3	0.15	0.1	0.05
Average	0.3	0.3	0.2	0.1	0.1
Heavy	0.1	0.2	0.4	0.2	0.1
Overweight	0.07	0.1	0.28	0.3	0.25
Obese	0.03	0.1	0.17	0.3	0.4

Table D: Accumulated state probs

1	0	0.4	0.7	0.85	0.95
2	0	0.3	0.6	0.8	0.9
3	0	0.1	0.3	0.7	0.9
4	0	0.07	0.17	0.45	0.75
5	0	0.03	0.13	0.3	0.6

Observation (O2): 5

Alarm(1) intervention: 10% change

	1	2	3	4	5	Total
1	**0.44**	**0.33**	**0.2**	**0.02**	**0.01**	1
2	**0.22**	**0.44**	**0.22**	**0.07**	**0.05**	1
3	**0.11**	**0.22**	**0.44**	**0.15**	**0.08**	1
4	**0.06**	**0.11**	**0.22**	**0.36**	**0.25**	1
5	**0.03**	**0.1**	**0.16**	**0.35**	**0.36**	1

Sj(t) = [**0.06** | **0.19** | **0.17** | **0.29** | **0.28**] X

Sj'(t) = [0.12 0.20 0.24 0.24 0.20] 〉

	O1	O2	O3	O4	O5	Total			
1	0.4	0.3	0.15	0.1	0.05	1	0.0058	O/sum =	0.0303
2	0.3	0.3	0.2	0.1	0.1	1	0.0203	O/sum =	0.1068
3	0.1	0.2	0.4	0.2	0.1	1	0.024	O/sum =	0.1265
4	0.07	0.1	0.28	0.3	0.25	1	0.0609	O/sum =	0.3206
5	0.03	0.1	0.17	0.3	0.4	1	0.0791	O/sum =	0.4159
						Sum	0.1901		

	S1	S2	S3	S4	S5	
Sk(t) = [	0.03	0.11	0.13	0.32	0.42	]
	S1	S2	S3	S4	S5	
	$41.73	$324.09	$697.82	$3,536.73	$9,176.21	$13,776.57

New-Alarm	Pre-Alarm	Final Alarm
2	1	2

Total Alarm 1	Total Alarm 2	Total Alarm 3
1	1	0

Update # 3: Season: Fall (December) Cost so far: $24,783.81

Figure A5: Demonstration of model Experiment II: Low-Policy Intervention in November

A.9 Experiment III: Moderate-Alarm (Moderate-Policy Intervention) for First Two Months

The moderate policy intervention model demonstrates a model with an intermediate implementation policy. The applied policy depends on the level of the alarm system. S5 is assigned to an alarm. The alarm's sensitivity is set to a range of 0.05 to 0.2 for the S5 value. The model follows a seasonality change through a transition matrix, during a one year period trial. There are ten independent trials for this model. In this appendix, only two months of one trial are demonstrated.

Update # 1: Season: Fall (October) Case III: Moderate-Policy Intervention (First Two Months)

Initial state:	1

Table A: State to state transition matrix

	Fit & healthy	Average	Heavy	Overweight	Obese	Total
Fit & healthy	0.45	0.3	0.15	0.075	0.025	1
Average	0.2	0.45	0.2	0.1	0.05	1
Heavy	0.1	0.15	0.45	0.2	0.1	1
Overweight	0.05	0.05	0.15	0.45	0.3	1
Obese	0.025	0.075	0.15	0.25	0.5	1

Table B: Accumulated state probs

	Fit & healthy	Average	Heavy	Overweight	Obese
1	0	0.45	0.75	0.9	0.975
2	0	0.2	0.65	0.85	0.95
3	0	0.1	0.25	0.7	0.9
4	0	0.05	0.1	0.25	0.7
5	0	0.025	0.1	0.25	0.5

New state:	3

Table C: State to observation matrix

	O1	O2	O3	O4	O5
Fit & healthy	0.4	0.3	0.15	0.1	0.05
Average	0.3	0.3	0.2	0.1	0.1
Heavy	0.1	0.2	0.4	0.2	0.1
Overweight	0.07	0.1	0.28	0.3	0.25
Obese	0.03	0.1	0.17	0.3	0.4

Table D: Accumulated state probs

	O1	O2	O3	O4	O5
1	0	0.4	0.7	0.85	0.95
2	0	0.3	0.6	0.8	0.9
3	0	0.1	0.3	0.7	0.9
4	0	0.07	0.17	0.45	0.75
5	0	0.03	0.13	0.3	0.6
rate	1	2	3	4	5

Observation (O1):	4

{ Initial state vector based on assumption}

	S1	S2	S3	S4	S5
Si(t) = [	**0.2**	**0.4**	**0.2**	**0.15**	**0.05**]

X

	S1	S2	S3	S4	S5
1	**0.4**	**0.3**	**0.2**	**0.075**	**0.025**
2	**0.2**	**0.4**	**0.25**	**0.1**	**0.05**
3	**0.1**	**0.2**	**0.4**	**0.2**	**0.1**
4	**0.05**	**0.1**	**0.2**	**0.4**	**0.25**
5	**0.025**	**0.075**	**0.15**	**0.35**	**0.4**

	S1	S2	S3	S4	S5
Si'(t) = [	**0.19**	**0.28**	**0.26**	**0.17**	**0.10**]

X

	O1	O2	O3	O4	O5	Total			
1	**0.4**	**0.3**	**0.15**	**0.1**	**0.05**	1	0.02	O/sum =	0.10
2	**0.3**	**0.3**	**0.2**	**0.1**	**0.1**	1	0.03	O/sum =	0.15
3	**0.1**	**0.2**	**0.4**	**0.2**	**0.1**	1	0.05	O/sum =	0.28
4	**0.07**	**0.1**	**0.28**	**0.3**	**0.25**	1	0.05	O/sum =	0.29
5	**0.03**	**0.1**	**0.17**	**0.3**	**0.4**	1	0.03	O/sum =	0.17
						Sum =	0.18		

New State

					S5
Sj(t) = [	**0.10**	**0.15**	**0.28**	**0.29**	**0.17**]

$144.00	$467.90	$1,571.64	$3,158.83	$3,753.97	**$9,096.34**

Alarm rate:	(no possibility of alarm 3)
1	

Total Alarm 1	Total Alarm 2	Total Alarm 3
1	**0**	**0**

Figure A6: Demonstration of model Experiment III: Moderate-Policy Intervention in October

Update # 2: Season: Fall (November) Case III: Moderate-Policy Intervention (First Two Months)

Previous state:	3
Previous Alarm:	1

Alarm-Type 1 Table A: State to state transition matrix

	Fit & healthy	Average	Heavy	Overweight	Obese	Total
Fit & healthy	0.44	0.33	0.2	0.02	0.01	1
Average	0.22	0.44	0.22	0.07	0.05	1
Heavy	0.11	0.22	0.44	0.15	0.08	1
Overweight	0.06	0.11	0.22	0.36	0.25	1
Obese	0.03	0.1	0.16	0.35	0.36	1

Table B: Accumulated state probs

1	0	0.44	0.77	0.97	0.99
2	0	0.22	0.66	0.88	0.95
3	0	0.11	0.33	0.77	0.92
4	0	0.06	0.17	0.39	0.75
5	0	0.03	0.13	0.29	0.64

Final new state:	3

Table C: State to observation matrix

	O1	O2	O3	O4	O5
Fit & healthy	0.4	0.3	0.15	0.1	0.05
Average	0.3	0.3	0.2	0.1	0.1
Heavy	0.1	0.2	0.4	0.2	0.1
Overweight	0.07	0.1	0.28	0.3	0.25
Obese	0.03	0.1	0.17	0.3	0.4

Table D: Accumulated state probs

1	0	0.4	0.7	0.85	0.95
2	0	0.3	0.6	0.8	0.9
3	0	0.1	0.3	0.7	0.9
4	0	0.07	0.17	0.45	0.75
5	0	0.03	0.13	0.3	0.6
rate					

Observation (O2):	4

Alarm(1) intervention: 10% change

	1	2	3	4	5
1	0.44	0.33	0.2	0.02	0.01
2	0.22	0.44	0.22	0.07	0.05
3	0.11	0.22	0.44	0.15	0.08
4	0.06	0.11	0.22	0.36	0.25
5	0.03	0.1	0.16	0.35	0.36

Sj(t) = [0.10 | 0.15 | 0.28 | 0.29 | 0.17] X

	O1	O2	O3	O4	O5	Total			
1	0.4	0.3	0.15	0.1	0.05	1	0.01	O/sum =	0.07
2	0.3	0.3	0.2	0.1	0.1	1	0.02	O/sum =	0.11
3	0.1	0.2	0.4	0.2	0.1	1	0.05	O/sum =	0.28
4	0.07	0.1	0.28	0.3	0.25	1	0.05	O/sum =	0.28
5	0.03	0.1	0.17	0.3	0.4	1	0.05	O/sum =	0.26
						Sum =	0.19		

	S1	S2	S3	S4	S5	
Sj'(t) = [	0.13	0.21	0.27	0.22	0.16	] X
Sk(t) = [	0.07	0.11	0.28	0.28	0.26	]
	$95.56	$336.25	$1,548.37	$3,124.61	$5,648.12	$10,752.91

New-Alarm	Pre-Alarm	Final Alarm
2	1	2

Total Alarm 1	Total Alarm 2	Total Alarm 3
1	1	0

Figure A7: Demonstration of model Experiment III: Moderate-Policy Intervention in November

A.10 Experiment IV: Extensive-Alarm (Extensive-Policy Intervention), Full Illustration

The extensive policy intervention model demonstrates a model with high implementation policies. The applied policy depends on the level of the alarm system. S5 is assigned to an alarm. The alarm's sensitivity is set to a range of 0.05 to 0.2 for the S5 value. In addition, the model in extensive policy is more sensitive compared to the moderate model. If the alarm level-2 repeats itself twice or if the last alarm was level-2, the model will follow the alarm level 3. The model follows a seasonality change through a transition matrix, during a one year period trial. There are ten independent trials for this model. In this appendix, a full version of a one trial is demonstrated.

Update # 1: **Season:** **Fall (October)** **Case IV: Extensive Policy**

Initial state: 1

Table A: State to state transition matrix

	Fit & Healthy	Average	Heavy	Overweight	Obese	Total
Fit & Healthy	0.45	0.3	0.15	0.075	0.025	1
Average	0.2	0.45	0.2	0.1	0.05	1
Heavy	0.1	0.15	0.45	0.2	0.1	1
Overweight	0.05	0.05	0.15	0.45	0.3	1
Obese	0.025	0.075	0.15	0.25	0.5	1

Table B: Accumulated state probs

S1	0	0.45	0.75	0.9	0.975
S2	0	0.2	0.65	0.85	0.95
S3	0	0.1	0.25	0.7	0.9
S4	0	0.05	0.1	0.25	0.7
S5	0	0.025	0.1	0.25	0.5

New state: 3

Table C: State to observation matrix

	O1	O2	O3	O4	O5
Fit & Healthy	0.4	0.3	0.15	0.1	0.05
Average	0.3	0.3	0.2	0.1	0.1
Heavy	0.1	0.2	0.4	0.2	0.1
Overweight	0.07	0.1	0.28	0.3	0.25
Obese	0.03	0.1	0.17	0.3	0.4

Table D: Accumulated state probs

S1	0	0.4	0.7	0.85	0.95
S2	0	0.3	0.6	0.8	0.9
S3	0	0.1	0.3	0.7	0.9
S4	0	0.07	0.17	0.45	0.75
S5	0	0.03	0.13	0.3	0.6

Observation (O1): 3

{ Initial state vector based on assumption}

	S1	S2	S3	S4	S5	
Si(t) = [	0.2	0.4	0.2	0.15	0.05	] X

	S1	S2	S3	S4	S5	Total
S1	0.4	0.3	0.2	0.075	0.025	1
S2	0.2	0.4	0.25	0.1	0.05	1
S3	0.1	0.2	0.4	0.2	0.1	1
S4	0.05	0.1	0.2	0.4	0.25	1
S5	0.025	0.075	0.15	0.35	0.4	1

Fall

	S1	S2	S3	S4	S5	
Si'(t) = [	0.19	0.28	0.26	0.17	0.10	] X

	O1	O2	O3	O4	O5	Total			
S1	0.4	0.3	0.15	0.1	0.05	1	0.03	O/sum =	0.11
S2	0.3	0.3	0.2	0.1	0.1	1	0.06	O/sum =	0.22
S3	0.1	0.2	0.4	0.2	0.1	1	0.10	O/sum =	0.41
S4	0.07	0.1	0.28	0.3	0.25	1	0.05	O/sum =	0.19
S5	0.03	0.1	0.17	0.3	0.4	1	0.02	O/sum =	0.07
						Sum =	0.25		

					S5	
Sj(t) = [	0.11	0.22	0.41	0.19	0.07	]

Alarm Rate (no possibility of alarm 3)

1

S1	S2	S3	S4	S5	Total
$154.45	$669.12	$2,247.53	$2,108.07	$1,521.04	$6,700.21

Total Alarm 1	Total Alarm 2	Total Alarm 3
1	0	0

Figure A8: Demonstration of model Experiment IV: Extensive-Policy Intervention for October

Update # 2: Season: Fall (November) Total Cost: $6,700.21

Last Updated Alarm:	1
Previous State:	3

Alarm(1) intervention: 10% change Table A:

	Fit & Healthy	Average	Heavy	Overweight	Obese	Total
Fit & Healthy	0.44	0.33	0.2	0.02	0.01	1
Average	0.22	0.44	0.22	0.07	0.05	1
Heavy	0.11	0.22	0.44	0.15	0.08	1
Overweight	0.06	0.11	0.22	0.36	0.25	1
Obese	0.03	0.1	0.16	0.35	0.36	1

Table B: Accumulated State Probability

S1	0	0.44	0.77	0.97	0.99
S2	0	0.22	0.66	0.88	0.95
S3	0	0.11	0.33	0.77	0.92
S4	0	0.06	0.17	0.39	0.75
S5	0	0.03	0.13	0.29	0.64

New State:	2

Table C: State to Observation Matrix

	O1	O2	O3	O4	O5
Fit & Healthy	0.4	0.3	0.15	0.1	0.05
Average	0.3	0.3	0.2	0.1	0.1
Heavy	0.1	0.2	0.4	0.2	0.1
Overweight	0.07	0.1	0.28	0.3	0.25
Obese	0.03	0.1	0.17	0.3	0.4

Observation (O2):	**2**

	S1	S2	S3	S4	S5	
Sj(t) = [	0.11	0.22	0.41	0.19	0.07	] X

	S1	S2	S3	S4	S5	
Sj'(t) = [	0.16	0.25	0.30	0.17	0.12	] X

New State					S5	
Sk(t) = [	0.22	0.36	0.29	0.08	0.06	]

S1	S2	S3	S4	S5	Total
$304.91	$1,080.68	$1,579.11	$894.17	$1,221.96	$5,080.83

Table D: Accumulated State Probability

	O1	O2	O3	O4	O5
S1	0	0.4	0.7	0.85	0.95
S2	0	0.3	0.6	0.8	0.9
S3	0	0.1	0.3	0.7	0.9
S4	0	0.07	0.17	0.45	0.75
S5	0	0.03	0.13	0.3	0.6
rate					

Alarm(1) intervention: 10% change

	1	**2**	**3**	4	5	Total
S1	0.44	0.33	0.2	0.02	0.01	**1**
S2	0.22	0.44	0.22	0.07	0.05	**1**
S3	0.11	0.22	0.44	0.15	0.08	**1**
S4	0.06	0.11	0.22	0.36	0.25	**1**
S5	0.03	0.1	0.16	0.35	0.36	**1**

	O1	O2	O3	O4	O5	Total			
S1	0.4	0.3	0.15	0.1	0.05	1	0.05	O/sum =	0.22
S2	0.3	0.3	0.2	0.1	0.1	1	0.08	O/sum =	0.36
S3	0.1	0.2	0.4	0.2	0.1	1	0.06	O/sum =	0.29
S4	0.07	0.1	0.28	0.3	0.25	1	0.02	O/sum =	0.08
S5	0.03	0.1	0.17	0.3	0.4	1	0.01	O/sum =	0.06
						Sum =	0.21		

New-Alarm	Pre-Alarm	Final Alarm
1	1	1

Total Alarm 1	Total Alarm 2	Total Alarm 3
2	0	0

Figure A9: Demonstration of model experiment IV: Extensive-Policy Intervention for Nov

Update # 3: **Season: Fall (December)** **Total Cost:** **$11,781.04**

Last Updated Alarm:	1
Previous State:	2

Alarm(1) intervention: 10% change — Table A:

	Fit & Healthy	Average	Heavy	Overweight	Obese	Total
Fit & Healthy	0.44	0.33	0.2	0.02	0.01	1
Average	0.22	0.44	0.22	0.07	0.05	1
Heavy	0.11	0.22	0.44	0.15	0.08	1
Overweight	0.06	0.11	0.22	0.36	0.25	1
Obese	0.03	0.1	0.16	0.35	0.36	1

Table B: Accumulated State Probability

S1	0	0.44	0.77	0.97	0.99	1
S2	0	0.22	0.66	0.88	0.95	2
S3	0	0.11	0.33	0.77	0.92	3
S4	0	0.06	0.17	0.39	0.75	4
S5	0	0.03	0.13	0.29	0.64	5

New State:	3

Table C: State to Observation Matrix

	O1	O2	O3	O4	O5
Fit & Healthy	0.4	0.3	0.15	0.1	0.05
Average	0.3	0.3	0.2	0.1	0.1
Heavy	0.1	0.2	0.4	0.2	0.1
Overweight	0.07	0.1	0.28	0.3	0.25
Obese	0.03	0.1	0.17	0.3	0.4

Table D: Accumulated State Probability

S1	0	0.4	0.7	0.85	0.95
S2	0	0.3	0.6	0.8	0.9
S3	0	0.1	0.3	0.7	0.9
S4	0	0.07	0.17	0.45	0.75
S5	0	0.03	0.13	0.3	0.6

Observation (O3):	2

	S1	S2	S3	S4	S5	
Sj(t) = [	0.22	0.36	0.29	0.08	0.06	] X

Alarm(1) intervention: 10% change

	1	2	3	4	5	Total
S1	0.44	0.33	0.2	0.02	0.01	1
S2	0.22	0.44	0.22	0.07	0.05	1
S3	0.11	0.22	0.44	0.15	0.08	1
S4	0.06	0.11	0.22	0.36	0.25	1
S5	0.03	0.1	0.16	0.35	0.36	1

	S1	S2	S3	S4	S5	
Sj'(t) = [	0.21	0.31	0.28	0.12	0.08	] X

	O1	O2	O3	O4	O5	Total			
S1	0.4	0.3	0.15	0.1	0.05	1	0.06	O/sum =	0.28
S2	0.3	0.3	0.2	0.1	0.1	1	0.09	O/sum =	0.40
S3	0.1	0.2	0.4	0.2	0.1	1	0.06	O/sum =	0.24
S4	0.07	0.1	0.28	0.3	0.25	1	0.01	O/sum =	0.05
S5	0.03	0.1	0.17	0.3	0.4	1	0.01	O/sum =	0.04
						Sum =	0.23		

					S5	
New State Sk(t) = [	0.28	0.40	0.24	0.05	0.04	]

New-Alarm	Pre-Alarm	Final Alarm	Total Alarm 1	Total Alarm 2	Total Alarm 3
0	1	1	3	0	0

S1	S2	S3	S4	S5	Total
$381.53	$1,206.59	$1,310.60	$575.53	$791.66	$4,265.91

Figure A10: Demonstration of model Experiment IV: Extensive-Policy Intervention for Dec

Update # 4: **Season: Winter (Jan)** **Total Cost:** **$16,046.95**

Last Updated Alarm:	1
Previous State:	3

Alarm(1) intervention: 10% change

	Fit & Healthy	Average	Heavy	Overweight	Obese	Total
Fit & Healthy	0.22	0.13	0.11	0.25	0.29	1
Average	0.11	0.11	0.17	0.3	0.31	1
Heavy	0.03	0.09	0.17	0.33	0.38	1
Overweight	0.022	0.022	0.066	0.39	0.5	1
Obese	0.011	0.011	0.033	0.345	0.6	1

S1	0	0.22	0.35	0.46	0.71	1
S2	0	0.11	0.22	0.39	0.69	2
S3	0	0.03	0.12	0.29	0.62	3
S4	0	0.022	0.044	0.11	0.5	4
S5	0	0.011	0.022	0.055	0.4	5

New State:	3

Table C: State to Observation Matrix

	O1	O2	O3	O4	O5
Fit & Healthy	0.4	0.3	0.15	0.1	0.05
Average	0.3	0.3	0.2	0.1	0.1
Heavy	0.1	0.2	0.4	0.2	0.1
Overweight	0.07	0.1	0.28	0.3	0.25
Obese	0.03	0.1	0.17	0.3	0.4

Table D: Accumulated State Probability

S1	0	0.4	0.7	0.85	0.95
S2	0	0.3	0.6	0.8	0.9
S3	0	0.1	0.3	0.7	0.9
S4	0	0.07	0.17	0.45	0.75
S5	0	0.03	0.13	0.3	0.6

Observation (O4):	3

Sj(t) = [

S1	S2	S3	S4	S5
0.28	0.40	0.24	0.05	0.04

] X

Alarm(1) intervention: 10% change

	1	2	3	4	5	Total
S1	0.22	0.13	0.11	0.25	0.29	1
S2	0.11	0.11	0.17	0.3	0.31	1
S3	0.03	0.09	0.17	0.33	0.38	1
S4	0.022	0.022	0.066	0.39	0.5	1
S5	0.011	0.011	0.033	0.345	0.6	1

Sj'(t) = [

S1	S2	S3	S4	S5
0.11	0.10	0.14	0.30	0.34

] X

S1	0.4	0.3	0.15	0.1	0.05	1	0.02	O/sum =	0.07
S2	0.3	0.3	0.2	0.1	0.1	1	0.02	O/sum =	0.09
S3	0.1	0.2	0.4	0.2	0.1	1	0.06	O/sum =	0.24
S4	0.07	0.1	0.28	0.3	0.25	1	0.08	O/sum =	0.35
S5	0.03	0.1	0.17	0.3	0.4	1	0.06	O/sum =	0.25
						Sum =	0.24		

Sk(t) = [

				S5
0.07	0.09	0.24	0.35	0.25

]

New-Alarm	Pre-Alarm	Final Alarm	Total Alarm 1	Total Alarm 2	Total Alarm 3
2	1	2	3	1	0

S1	S2	S3	S4	S5	Total
$99.01	$263.15	$1,333.68	$3,910.65	$5,411.33	$11,017.82

Figure A11: Demonstration of model Experiment IV: Extensive-Policy Intervention for January

Update # 5: **Season:** **Winter (Feb)** **Total Cost:** **$27,064.77**

Last Updated Alarm:	1
Previous State:	3

Alarm(2) intervention: 25% change

	Fit & Healthy	Average	Heavy	Overweight	Obese	Total
Fit & Healthy	0.25	0.15	0.13	0.20	0.28	1
Average	0.13	0.13	0.18	0.22	0.35	1
Heavy	0.03	0.10	0.19	0.30	0.38	1
Overweight	0.03	0.03	0.08	0.38	0.49	1
Obese	0.01	0.01	0.04	0.34	0.60	1

S1	0	0.25	0.4	0.525	0.725	1
S2	0	0.125	0.25	0.43	0.65	2
S3	0	0.03	0.13	0.32	0.62	3
S4	0	0.025	0.053	0.133	0.513	4
S5	0	0.0125	0.025	0.065	0.4	5

New State:	4

Table C: State to Observation Matrix

	O1	O2	O3	O4	O5
Fit & Healthy	0.4	0.3	0.15	0.1	0.05
Average	0.3	0.3	0.2	0.1	0.1
Heavy	0.1	0.2	0.4	0.2	0.1
Overweight	0.07	0.1	0.28	0.3	0.25
Obese	0.03	0.1	0.17	0.3	0.4

Table D: Accumulated State Probability

S1	0	0.4	0.7	0.85	0.95
S2	0	0.3	0.6	0.8	0.9
S3	0	0.1	0.3	0.7	0.9
S4	0	0.07	0.17	0.45	0.75
S5	0	0.03	0.13	0.3	0.6

Observation (O5):	2

	S1	S2	S3	S4	S5	
Sj(t) = [	0.07	0.09	0.24	0.35	0.25	] X

Alarm(2) intervention: 25% change

	1	2	3	4	5	Total
S1	0.25	0.15	0.13	0.20	0.28	1
S2	0.13	0.13	0.18	0.22	0.35	1
S3	0.03	0.10	0.19	0.30	0.38	1
S4	0.03	0.03	0.08	0.38	0.49	1
S5	0.01	0.01	0.04	0.34	0.60	1

	S1	S2	S3	S4	S5	
Sj'(t) = [	0.05	0.06	0.11	0.32	0.46	] X

S1	0.4	0.3	0.15	0.1	0.05	1	0.01	O/sum =	0.11
S2	0.3	0.3	0.2	0.1	0.1	1	0.02	O/sum =	0.13
S3	0.1	0.2	0.4	0.2	0.1	1	0.02	O/sum =	0.16
S4	0.07	0.1	0.28	0.3	0.25	1	0.03	O/sum =	0.24
S5	0.03	0.1	0.17	0.3	0.4	1	0.05	O/sum =	0.35
						Sum =	0.13		

					S5	
New State Sk(t) = [	0.11	0.13	0.16	0.24	0.35	]

New-Alarm	Pre-Alarm	Final Alarm	Total Alarm 1	Total Alarm 2	Total Alarm 3
2	2	3	3	1	1

S1	S2	S3	S4	S5	Total
$150.10	$404.64	$906.89	$2,693.77	$7,705.90	$11,861.29

Figure A12: Demonstration of model Experiment IV: Extensive-Policy Intervention for Feb

Update # 6:		Season: Winter (March)	Total Cost:	$38,926.06

Last Updated Alarm:	3
Previous State:	4

Alarm(3) intervention: 40% change

	Fit & Healthy	Average	Heavy	Overweight	Obese	Total
Fit & Healthy	0.3	0.16	0.14	0.22	0.18	1
Average	0.14	0.14	0.19	0.25	0.28	1
Heavy	0.03	0.1	0.2	0.3	0.37	1
Overweight	0.03	0.04	0.08	0.38	0.47	1
Obese	0.02	0.02	0.05	0.4	0.51	1

S1	0	0.3	0.46	0.6	0.82	1
S2	0	0.14	0.28	0.47	0.72	2
S3	0	0.03	0.13	0.33	0.63	3
S4	0	0.03	0.07	0.15	0.53	4
S5	0	0.02	0.04	0.09	0.49	5

New State:	4

Table C: State to Observation Matrix

	O1	O2	O3	O4	O5
Fit & Healthy	0.4	0.3	0.15	0.1	0.05
Average	0.3	0.3	0.2	0.1	0.1
Heavy	0.1	0.2	0.4	0.2	0.1
Overweight	0.07	0.1	0.28	0.3	0.25
Obese	0.03	0.1	0.17	0.3	0.4

Observation (O6):	3

Table D: Accumulated State Probability

S1	0	0.4	0.7	0.85	0.95
S2	0	0.3	0.6	0.8	0.9
S3	0	0.1	0.3	0.7	0.9
S4	0	0.07	0.17	0.45	0.75
S5	0	0.03	0.13	0.3	0.6
rate	1	2	3	4	5

	S1	S2	S3	S4	S5	
Sj(t) = [	0.11	0.13	0.16	0.24	0.35	] X

Alarm(3) intervention: 40% change

	1	2	3	4	5	Total
S1	0.3	0.16	0.14	0.22	0.18	1
S2	0.14	0.14	0.19	0.25	0.28	1
S3	0.03	0.1	0.2	0.3	0.37	1
S4	0.03	0.04	0.08	0.38	0.47	1
S5	0.02	0.02	0.05	0.4	0.51	1

	S1	S2	S3	S4	S5	
Sj'(t) = [	0.07	0.07	0.11	0.34	0.41	] X

S1	0.4	0.3	0.15	0.1	0.05	1	0.01	O/sum =	0.05
S2	0.3	0.3	0.2	0.1	0.1	1	0.01	O/sum =	0.06
S3	0.1	0.2	0.4	0.2	0.1	1	0.04	O/sum =	0.19
S4	0.07	0.1	0.28	0.3	0.25	1	0.09	O/sum =	0.41
S5	0.03	0.1	0.17	0.3	0.4	1	0.07	O/sum =	0.30
						Sum =	0.23		

					S5	
New State Sk(t) = [	0.05	0.06	0.19	0.41	0.30	]

New-Alarm	Pre-Alarm	Final Alarm	Total Alarm 1	Total Alarm 2	Total Alarm 3
2	3	3	3	1	2

S1	S2	S3	S4	S5	Total
$62.55	$180.14	$1,044.29	$4,488.56	$6,600.40	$12,375.93

Figure A13: Demonstration of model Experiment IV: Extensive-Policy Intervention for March

Update # 7: **Season: Spring (April)** **Total Cost:** **$51,301.99**

Last Updated Alarm:	3
Previous State:	4

Alarm(3) intervention: 40% change

	Fit & Healthy	Average	Heavy	Overweight	Obese	Total
Fit & Healthy	0.4	0.3	0.18	0.07	0.05	1
Average	0.3	0.25	0.2	0.1	0.15	1
Heavy	0.15	0.18	0.22	0.25	0.2	1
Overweight	0.1	0.08	0.15	0.29	0.38	1
Obese	0.08	0.1	0.12	0.3	0.4	1

S1	0	0.4	0.7	0.88	0.95	1
S2	0	0.3	0.55	0.75	0.85	2
S3	0	0.15	0.33	0.55	0.8	3
S4	0	0.1	0.18	0.33	0.62	4
S5	0	0.08	0.18	0.3	0.6	5

New State:	2

Table C: State to Observation Matrix

	O1	O2	O3	O4	O5
1	0.4	0.3	0.15	0.1	0.05
2	0.3	0.3	0.2	0.1	0.1
3	0.1	0.2	0.4	0.2	0.1
4	0.07	0.1	0.28	0.3	0.25
5	0.03	0.1	0.17	0.3	0.4

Table D: Accumulated State Probability

S1	0	0.4	0.7	0.85	0.95
S2	0	0.3	0.6	0.8	0.9
S3	0	0.1	0.3	0.7	0.9
S4	0	0.07	0.17	0.45	0.75
S5	0	0.03	0.13	0.3	0.6
rate	1	2	3	4	5

Observation (O7):	3

	S1	S2	S3	S4	S5	
Sj(t) = [	0.05	0.06	0.19	0.41	0.30	] X

Alarm(3) intervention: 40% change

	1	2	3	4	5	Total
S1	0.4	0.3	0.18	0.07	0.05	1
S2	0.3	0.25	0.2	0.1	0.15	1
S3	0.15	0.18	0.22	0.25	0.2	1
S4	0.1	0.08	0.15	0.29	0.38	1
S5	0.08	0.1	0.12	0.3	0.4	1

	S1	S2	S3	S4	S5	
Sj'(t) = [	0.13	0.12	0.16	0.26	0.32	] X

S1	0.4	0.3	0.15	0.1	0.05	1	0.02	O/sum =	0.08
S2	0.3	0.3	0.2	0.1	0.1	1	0.02	O/sum =	0.11
S3	0.1	0.2	0.4	0.2	0.1	1	0.06	O/sum =	0.27
S4	0.07	0.1	0.28	0.3	0.25	1	0.07	O/sum =	0.31
S5	0.03	0.1	0.17	0.3	0.4	1	0.05	O/sum =	0.23
						Sum =	0.24		

	S1	S2	S3	S4	S5	
New State Sk(t) = [	0.08	0.11	0.27	0.31	0.23	]

New-Alarm	Pre-Alarm	Final Alarm	Total Alarm 1	Total Alarm 2	Total Alarm 3
2	3	3	3	1	3

S1	S2	S3	S4	S5	Total
$112.70	$320.40	$1,478.42	$3,447.51	$5,123.20	$10,482.22

Figure A14: Demonstration of model Experiment IV: Extensive-Policy Intervention for April

Update # 8: **Season: Spring (May)** **Total Cost:** **$61,784.21**

Last Updated Alarm:	3
Previous State:	2

Alarm(3) intervention: 40% change

	Fit & Healthy	Average	Heavy	Overweight	Obese	Total
Fit & Healthy	0.4	0.3	0.18	0.07	0.05	1
Average	0.3	0.25	0.2	0.1	0.15	1
Heavy	0.15	0.18	0.22	0.25	0.2	1
Overweight	0.1	0.08	0.15	0.29	0.38	1
Obese	0.08	0.1	0.12	0.3	0.4	1

S1	0	0.4	0.7	0.88	0.95	1
S2	0	0.3	0.55	0.75	0.85	2
S3	0	0.15	0.33	0.55	0.8	3
S4	0	0.1	0.18	0.33	0.62	4
S5	0	0.08	0.18	0.3	0.6	5

New State:		1

Table C: State to Observation Matrix

	O1	O2	O3	O4	O5
Fit & Healthy	0.4	0.3	0.15	0.1	0.05
Average	0.3	0.3	0.2	0.1	0.1
Heavy	0.1	0.2	0.4	0.2	0.1
Overweight	0.07	0.1	0.28	0.3	0.25
Obese	0.03	0.1	0.17	0.3	0.4

Observation (O8):	1

Table D: Accumulated State Probability

S1	0	0.4	0.7	0.85	0.95
S2	0	0.3	0.6	0.8	0.9
S3	0	0.1	0.3	0.7	0.9
S4	0	0.07	0.17	0.45	0.75
S5	0	0.03	0.13	0.3	0.6
rate	1	2	3	4	5

Sj(t) = [

S1	S2	S3	S4	S5
0.08	0.11	0.27	0.31	0.23

] X

Alarm(3) intervention: 40% change

	1	2	3	4	5	Total
S1	0.4	0.3	0.18	0.07	0.05	1
S2	0.3	0.25	0.2	0.1	0.15	1
S3	0.15	0.18	0.22	0.25	0.2	1
S4	0.1	0.08	0.15	0.29	0.38	1
S5	0.08	0.1	0.12	0.3	0.4	1

Sj'(t) = [

S1	S2	S3	S4	S5
0.15	0.15	0.17	0.24	0.29

] X

S1	0.4	0.3	0.15	0.1	0.05	1	0.06	O/sum =	0.42
S2	0.3	0.3	0.2	0.1	0.1	1	0.04	O/sum =	0.30
S3	0.1	0.2	0.4	0.2	0.1	1	0.02	O/sum =	0.11
S4	0.07	0.1	0.28	0.3	0.25	1	0.02	O/sum =	0.11
S5	0.03	0.1	0.17	0.3	0.4	1	0.01	O/sum =	0.06
						Sum =	0.15		

New State
Sk(t) = [

				S5
0.42	0.30	0.11	0.11	0.06

]

New-Alarm	Pre-Alarm	Final Alarm	Total Alarm 1	Total Alarm 2	Total Alarm 3
1	3	3	3	1	4

S1	S2	S3	S4	S5	Total
$573.39	$903.15	$629.59	$1,266.44	$1,270.86	$4,643.44

Figure A15: Demonstration of model Experiment IV: Extensive-Policy Intervention for May

Update # 9: Season: Spring (June) Total Cost: $66,427.65

Last Updated Alarm:	3
Previous State:	1

Alarm(3) intervention: 40% change

	Fit & Healthy	Average	Heavy	Overweight	Obese	Total
Fit & Healthy	0.4	0.3	0.18	0.07	0.05	1
Average	0.3	0.25	0.2	0.1	0.15	1
Heavy	0.15	0.18	0.22	0.25	0.2	1
Overweight	0.1	0.08	0.15	0.29	0.38	1
Obese	0.08	0.1	0.12	0.3	0.4	1

S1	0	0.4	0.7	0.88	0.95	1
S2	0	0.3	0.55	0.75	0.85	2
S3	0	0.15	0.33	0.55	0.8	3
S4	0	0.1	0.18	0.33	0.62	4
S5	0	0.08	0.18	0.3	0.6	5

New State:	3

Table C: State to Observation Matrix

	O1	O2	O3	O4	O5
Fit & Healthy	0.4	0.3	0.15	0.1	0.05
Average	0.3	0.3	0.2	0.1	0.1
Heavy	0.1	0.2	0.4	0.2	0.1
Overweight	0.07	0.1	0.28	0.3	0.25
Obese	0.03	0.1	0.17	0.3	0.4

Table D: Accumulated State Probability

S1	0	0.4	0.7	0.85	0.95
S2	0	0.3	0.6	0.8	0.9
S3	0	0.1	0.3	0.7	0.9
S4	0	0.07	0.17	0.45	0.75
S5	0	0.03	0.13	0.3	0.6
rate	1	2	3	4	5

Observation (O9):	3

Alarm(3) intervention: 40% change

	1	2	3	4	5	Total
S1	0.4	0.3	0.18	0.07	0.05	1
S2	0.3	0.25	0.2	0.1	0.15	1
S3	0.15	0.18	0.22	0.25	0.2	1
S4	0.1	0.08	0.15	0.29	0.38	1
S5	0.08	0.1	0.12	0.3	0.4	1

	S1	S2	S3	S4	S5	
Sj(t) = [	0.42	0.30	0.11	0.11	0.06	] X

S1	0.4	0.3	0.15	0.1	0.05	1	0.04	O/sum =	0.19
S2	0.3	0.3	0.2	0.1	0.1	1	0.05	O/sum =	0.21
S3	0.1	0.2	0.4	0.2	0.1	1	0.07	O/sum =	0.32
S4	0.07	0.1	0.28	0.3	0.25	1	0.04	O/sum =	0.17
S5	0.03	0.1	0.17	0.3	0.4	1	0.03	O/sum =	0.12
						Sum =	0.23		

	S1	S2	S3	S4	S5	
Sj'(t) = [	0.29	0.23	0.18	0.14	0.15	] X

New-Alarm	Pre-Alarm	Final Alarm	Total Alarm 1	Total Alarm 2	Total Alarm 3
1	3	3	3	1	5

New State					S5	
Sk(t) = [	0.19	0.21	0.32	0.17	0.12	]

S1	S2	S3	S4	S5	Total
$261.27	$622.66	$1,771.70	$1,863.96	$2,541.46	$7,061.04

Figure A16: Demonstration of model Experiment IV: Extensive-Policy Intervention for June

Update # 10: Season: ımmer (July) Total Cost: $73,488.69

Last Updated Alarm:	3
Previous State:	3

Alarm(3) intervention: 40% change

	Fit & Healthy	Average	Heavy	Overweight	Obese	Total
Fit & Healthy	0.77	0.22	0.00	0.00	0.00	1
Average	0.66	0.33	0.00	0.00	0.00	1
Heavy	0.55	0.33	0.02	0.08	0.02	1
Overweight	0.48	0.35	0.07	0.05	0.05	1
Obese	0.40	0.25	0.08	0.12	0.15	1

S1	0	0.77	0.99	1.00	1.00	1
S2	0	0.66	0.99	1.00	1.00	2
S3	0	0.55	0.88	0.90	0.98	3
S4	0	0.48	0.83	0.90	0.95	4
S5	0	0.40	0.65	0.73	0.85	5

New State:	4

Table C: State to Observation Matrix

	O1	O2	O3	O4	O5
Fit & Healthy	0.4	0.3	0.15	0.1	0.05
Average	0.3	0.3	0.2	0.1	0.1
Heavy	0.1	0.2	0.4	0.2	0.1
Overweight	0.07	0.1	0.28	0.3	0.25
Obese	0.03	0.1	0.17	0.3	0.4

Observation (O10):	5

Table D: Accumulated State Probability

S1	0	0.4	0.7	0.85	0.95
S2	0	0.3	0.6	0.8	0.9
S3	0	0.1	0.3	0.7	0.9
S4	0	0.07	0.17	0.45	0.75
S5	0	0.03	0.13	0.3	0.6
rate	1	2	3	4	5

Sj(t) = [

S1	S2	S3	S4	S5
0.19	0.21	0.32	0.17	0.12

] X

Alarm(3) intervention: 40% change

	1	2	3	4	5	Total
S1	0.77	0.22	0.00	0.00	0.00	1
S2	0.66	0.33	0.00	0.00	0.00	1
S3	0.55	0.33	0.02	0.08	0.02	1
S4	0.48	0.35	0.07	0.05	0.05	1
S5	0.40	0.25	0.08	0.12	0.15	1

Sj'(t) = [

S1	S2	S3	S4	S5
0.59	0.30	0.03	0.05	0.03

] X

S1	0.4	0.3	0.15	0.1	0.05	1	0.03	O/sum =	0.33
S2	0.3	0.3	0.2	0.1	0.1	1	0.03	O/sum =	0.35
S3	0.1	0.2	0.4	0.2	0.1	1	0.00	O/sum =	0.03
S4	0.07	0.1	0.28	0.3	0.25	1	0.01	O/sum =	0.14
S5	0.03	0.1	0.17	0.3	0.4	1	0.01	O/sum =	0.15
						Sum =	0.09		

New State
Sk(t) = [

S1	S2	S3	S4	S5
0.33	0.35	0.03	0.14	0.15

]

New-Alarm	Pre-Alarm	Final Alarm	Total Alarm 1	Total Alarm 2	Total Alarm 3
1	3	3	3	1	6

S1	S2	S3	S4	S5	Total
$458.95	$1,052.30	$177.18	$1,536.10	$3,287.91	$6,512.43

Figure A17: Demonstration of model Experiment IV: Extensive-Policy Intervention for July

Update # 11: **Season: nmer (August)** **Total Cost:** **$80,001.12**

Last Updated Alarm:	3
Previous State:	4

Alarm(3) intervention: 40% change

	Fit & Healthy	Average	Heavy	Overweight	Obese	Total
Fit & Healthy	0.77	0.22	0.00	0.00	0.00	1
Average	0.66	0.33	0.00	0.00	0.00	1
Heavy	0.55	0.33	0.02	0.08	0.02	1
Overweight	0.48	0.35	0.07	0.05	0.05	1
Obese	0.40	0.25	0.08	0.12	0.15	1

S1	0	0.77	0.99	1.00	1.00	1
S2	0	0.66	0.99	1.00	1.00	2
S3	0	0.55	0.88	0.90	0.98	3
S4	0	0.48	0.83	0.90	0.95	4
S5	0	0.40	0.65	0.73	0.85	5

New State:	5

Table C: State to Observation Matrix

	O1	O2	O3	O4	O5
Fit & Healthy	0.4	0.3	0.15	0.1	0.05
Average	0.3	0.3	0.2	0.1	0.1
Heavy	0.1	0.2	0.4	0.2	0.1
Overweight	0.07	0.1	0.28	0.3	0.25
Obese	0.03	0.1	0.17	0.3	0.4

Table D: Accumulated State Probability

S1	0	0.4	0.7	0.85	0.95
S2	0	0.3	0.6	0.8	0.9
S3	0	0.1	0.3	0.7	0.9
S4	0	0.07	0.17	0.45	0.75
S5	0	0.03	0.13	0.3	0.6
rate	1	2	3	4	5

Observation (O11):	5

	S1	S2	S3	S4	S5	
Sj(t) = [	0.33	0.35	0.03	0.14	0.15	] X

Alarm(3) intervention: 40% change

	1	2	3	4	5	Total
S1	0.77	0.22	0.00	0.00	0.00	1
S2	0.66	0.33	0.00	0.00	0.00	1
S3	0.55	0.33	0.02	0.08	0.02	1
S4	0.48	0.35	0.07	0.05	0.05	1
S5	0.40	0.25	0.08	0.12	0.15	1

	S1	S2	S3	S4	S5	
Sj'(t) = [	0.63	0.29	0.02	0.03	0.03	] X

S1	0.4	0.3	0.15	0.1	0.05	1	0.03	O/si
S2	0.3	0.3	0.2	0.1	0.1	1	0.03	O/si
S3	0.1	0.2	0.4	0.2	0.1	1	0.00	O/si
S4	0.07	0.1	0.28	0.3	0.25	1	0.01	O/si
S5	0.03	0.1	0.17	0.3	0.4	1	0.01	O/si
						Sum =	0.08	

					S5	
New State Sk(t) = [	0.38	0.35	0.03	0.09	0.15	]

New-Alarm	Pre-Alarm	Final Alarm	Total Alarm 1	Total Alarm 2	Total Alarm 3
1	3	3	3	1	7

S1	S2	S3	S4	S5	Total
$527.85	$1,059.24	$158.73	$977.07	$3,326.70	$6,049.60

Figure A18: Demonstration of model Experiment IV: Extensive-Policy Intervention for Aug

Update # 12: **Season: ner (September)** **Total Cost:** **$86,050.72**

Last Updated Alarm:	3
Previous State:	5

Alarm(3) intervention: 40% change

	Fit & Healthy	Average	Heavy	Overweight	Obese	Total
Fit & Healthy	0.77	0.22	0.00	0.00	0.00	1
Average	0.66	0.33	0.00	0.00	0.00	1
Heavy	0.55	0.33	0.02	0.08	0.02	1
Overweight	0.48	0.35	0.07	0.05	0.05	1
Obese	0.40	0.25	0.08	0.12	0.15	1

S1	0	0.77	0.99	1.00	1.00	
S2	0	0.66	0.99	1.00	1.00	1
S3	0	0.55	0.88	0.90	0.98	2
S4	0	0.48	0.83	0.90	0.95	3
S5	0	0.40	0.65	0.73	0.85	4

New State:	2

Table C: State to Observation Matrix

	O1	O2	O3	O4	O5
Fit & Healthy	0.4	0.3	0.15	0.1	0.05
Average	0.3	0.3	0.2	0.1	0.1
Heavy	0.1	0.2	0.4	0.2	0.1
Overweight	0.07	0.1	0.28	0.3	0.25
Obese	0.03	0.1	0.17	0.3	0.4

Observation (O12):	2

Table D: Accumulated State Probability

S1	0	0.4	0.7	0.85	0.95
S2	0	0.3	0.6	0.8	0.9
S3	0	0.1	0.3	0.7	0.9
S4	0	0.07	0.17	0.45	0.75
S5	0	0.03	0.13	0.3	0.6
rate	1	2	3	4	5

Alarm(3) intervention: 40% change

	1	2	3	4	5	Total
S1	0.77	0.22	0.00	0.00	0.00	1
S2	0.66	0.33	0.00	0.00	0.00	1
S3	0.55	0.33	0.02	0.08	0.02	1
S4	0.48	0.35	0.07	0.05	0.05	1
S5	0.40	0.25	0.08	0.12	0.15	1

	S1	S2	S3	S4	S5	
Sj(t) = [	0.38	0.35	0.03	0.09	0.15	] X

	S1	S2	S3	S4	S5	
Sj'(t) = [	0.64	0.28	0.02	0.03	0.03	] X

S1	0.4	0.3	0.15	0.1	0.05	1	0.19	O/sum =	0.67
S2	0.3	0.3	0.2	0.1	0.1	1	0.08	O/sum =	0.29
S3	0.1	0.2	0.4	0.2	0.1	1	0.00	O/sum =	0.01
S4	0.07	0.1	0.28	0.3	0.25	1	0.00	O/sum =	0.01
S5	0.03	0.1	0.17	0.3	0.4	1	0.00	O/sum =	0.01
						Sum =	0.29		

New State					S5	
Sk(t) = [	0.67	0.29	0.01	0.01	0.01	]

S1	S2	S3	S4	S5	Total
$928.34	$890.00	$78.19	$102.42	$220.73	$2,219.68

New-Alarm	Pre-Alarm	Final Alarm	Total Alarm 1	Total Alarm 2	Total Alarm 3
0	3	3	3	1	8

Total cost: **$88,270.40**

Figure A19: Demonstration of model Experiment IV: Extensive-Policy Intervention for Sept

APPENDIX B :
Comparison Results

Appendix 2 demonstrates the final outputs and the results of all four Experiments, in the example obesity case study. The four experiments are:

I. No-Policy intervention (No-alarm)
II. Low-Policy intervention (Low-alarm)
III. Moderate-Policy intervention, (Moderate-alarm)
IV. Extensive-Policy intervention

All results, given as tables of probability matrices and as graphics, came from ten (10) trials each for a period of 12 months (one year). The corresponding graphs for each Experiment are illustrated below. Also, the final averages for all 10 trials of each Experiment are demonstrated for the purposes of comparison.

B.1 Experiment I: No-Policy Intervention

The following figure illustrates the final annual probability state transitions of ten trials for the Experiment I, No-policy intervention:

Sheet 1

Periods	Fit & healthy S1	Average S2	Heavy S3	Overweight S4	Obese S5
Oct	0.377452818	0.418072741	0.128733908	0.060367454	0.015373078
Nov	0.153764176	0.256119778	0.401881887	0.143461395	0.044772764
Dec	0.350011031	0.401647471	0.157920392	0.072409369	0.018011737
Jan	0.222982312	0.187047014	0.160122119	0.199819224	0.230029331
Feb	0.308804897	0.205417106	0.09890163	0.248698208	0.138178159
Mar	0.059449219	0.062850168	0.167205103	0.404710158	0.305785352
Apr	0.028078963	0.031386746	0.112069024	0.343467339	0.484997929
May	0.237864278	0.209481106	0.150389786	0.249712077	0.152552754
Jun	0.088076387	0.11498829	0.257544891	0.295705317	0.243685116
Jul	0.459744905	0.38187018	0.091877877	0.032459275	0.034047763
Aug	0.554857728	0.385770842	0.041392593	0.009480561	0.008498277
Sep	0.570837235	0.383407478	0.033509251	0.006436033	0.005810003

Sheet 2

Periods	Fit & healthy S1	Average S2	Heavy S3	Overweight S4	Obese S5	Periods
Oct	0.258266819	0.381413911	0.234891676	0.078677309	0.046750285	Oct
Nov	0.397582277	0.413084339	0.125908313	0.050908415	0.012516656	Nov
Dec	0.322603977	0.3961604	0.205123973	0.050631826	0.025479825	Dec
Jan	0.372210475	0.244741013	0.107284635	0.184478324	0.091285552	Jan
Feb	0.041927119	0.032666008	0.08240026	0.382033241	0.460973371	Feb
Mar	0.009008002	0.009568514	0.041040435	0.385557292	0.554825757	Mar
Apr	0.090016363	0.106593773	0.19214777	0.24999566	0.361246433	Apr
May	0.033787679	0.037271438	0.113110898	0.341853661	0.473976324	May
Jun	0.034730792	0.053710396	0.224406405	0.368538491	0.318613915	Jun
Jul	0.555446648	0.358965913	0.047971601	0.02536251	0.012253327	Jul
Aug	0.65094223	0.328006294	0.015071345	0.004305219	0.001674911	Aug
Sep	0.582080629	0.378739044	0.02916414	0.005140919	0.004875269	Sep

Sheet 4

Periods	Fit & healthy S1	Average S2	Heavy S3	Overweight S4	Obese S5
Oct	0.258266819	0.381413911	0.234891676	0.078677309	0.046750285
Nov	0.397582277	0.413084339	0.125908313	0.050908415	0.012516656
Dec	0.322603977	0.3961604	0.205123973	0.050631826	0.025479825
Jan	0.022035939	0.038638339	0.05081249	0.312047183	0.576466049
Feb	0.007443451	0.00789296	0.036102701	0.37977231	0.568788578
Mar	0.11063592	0.090980854	0.080163329	0.437646765	0.280573131
Apr	0.016043025	0.032578256	0.053738896	0.273948566	0.623691257
May	0.007434431	0.017717498	0.04261617	0.283219905	0.649011997
Jun	0.023671114	0.038606994	0.204433684	0.39160573	0.341682478
Jul	0.433946421	0.377185996	0.103214477	0.039755292	0.045897814
Aug	0.413248325	0.386876594	0.13124617	0.044120913	0.024507997
Sep	0.54799447	0.387569041	0.04551125	0.010508047	0.008417193

Sheet 5

Periods	Fit & healthy S1	Average S2	Heavy S3	Overweight S4	Obese S5	Periods
Oct	0.104426003	0.154218534	0.284923928	0.286307054	0.170124481	Oct
Nov	0.060001647	0.09595756	0.256892345	0.318753332	0.268395116	Nov
Dec	0.15732495	0.274616153	0.278175511	0.164387793	0.125495593	Dec
Jan	0.026516613	0.028093231	0.086256612	0.38428021	0.474853334	Jan
Feb	0.139823851	0.119248044	0.089629221	0.402056668	0.249242216	Feb
Mar	0.019155834	0.017025056	0.056433742	0.389993084	0.517392284	Mar
Apr	0.028140006	0.043512094	0.216177141	0.379839807	0.332330951	Apr
May	0.011902622	0.028571484	0.054007549	0.278589017	0.626929328	May
Jun	0.026126773	0.041986576	0.207244119	0.387467924	0.337174609	Jun
Jul	0.230956396	0.200357718	0.163627739	0.188393639	0.216664508	Jul
Aug	0.326496484	0.335576399	0.186920231	0.089983263	0.061023623	Aug
Sep	0.528778493	0.387721115	0.056003413	0.01489165	0.012605329	Sep

Sheet 7

Periods	Fit & healthy S1	Average S2	Heavy S3	Overweight S4	Obese S5
Oct	0.258266819	0.381413911	0.234891676	0.078677309	0.046750285
Nov	0.397582277	0.413084339	0.125908313	0.050908415	0.012516656
Dec	0.104022516	0.255481051	0.198424508	0.244890807	0.197181118
Jan	0.010187398	0.021651515	0.035304333	0.304770961	0.628085794
Feb	0.00599848	0.006450758	0.032406688	0.378381017	0.576763057
Mar	0.042675922	0.046624573	0.083464049	0.330892961	0.496342495
Apr	0.035588693	0.053421116	0.220537746	0.369969059	0.320483386
May	0.012696976	0.030095646	0.05474966	0.278153975	0.624303744
Jun	0.007232428	0.017386696	0.042545266	0.283312233	0.649523376
Jul	0.195893823	0.176048503	0.139141773	0.199657298	0.289258602
Aug	0.590818551	0.348416687	0.033998301	0.017638531	0.009127931
Sep	0.654665275	0.325930734	0.014040789	0.003835903	0.001527298

Sheet 8

Periods	Fit & healthy S1	Average S2	Heavy S3	Overweight S4	Obese S5	Periods
Oct	0.258266819	0.381413911	0.234891676	0.078677309	0.046750285	Oct
Nov	0.276730116	0.383360069	0.233696682	0.067493148	0.038719986	Nov
Dec	0.283040489	0.385266471	0.231590828	0.064211736	0.035890477	Dec
Jan	0.040790763	0.037272076	0.101172382	0.379069744	0.441695034	Jan
Feb	0.066423854	0.073620986	0.103993908	0.311289333	0.444671919	Feb
Mar	0.011931503	0.012262208	0.046656891	0.382853076	0.546296321	Mar
Apr	0.007070389	0.016660135	0.043749818	0.281782862	0.650736795	Apr
May	0.006362159	0.01561479	0.041461801	0.283883992	0.652677258	May
Jun	0.023210114	0.038019989	0.204018117	0.392317239	0.34243454	Jun
Jul	0.433748045	0.377147984	0.103300961	0.039812032	0.045990977	Jul
Aug	0.413185745	0.386847581	0.131288406	0.044150288	0.024527979	Aug
Sep	0.410687968	0.387288286	0.136455791	0.044113488	0.021454467	Sep

Sheet 3

Periods	Fit & healthy S1	Average S2	Heavy S3	Overweight S4	Obese S5
Oct	0.258266819	0.38141391	0.234891676	0.078677309	0.046750285
Nov	0.397582277	0.41308434	0.125908313	0.050908415	0.012516656
Dec	0.158024299	0.25874023	0.401911623	0.138888334	0.042435519
Jan	0.026659429	0.03111025	0.09660393	0.38749597	0.458130421
Feb	0.00798662	0.0092752	0.041376075	0.386158015	0.555204087
Mar	0.002606777	0.00579162	0.015119936	0.288688341	0.687793324
Apr	0.005397129	0.0133603	0.03979442	0.284429098	0.657019051
May	0.006128293	0.01512115	0.041167502	0.284009632	0.653573422
Jun	0.023103042	0.03788229	0.203916098	0.39248592	0.342612653
Jul	0.433701567	0.37713892	0.103321113	0.03982537	0.046013029
Aug	0.636782794	0.3353638	0.018971071	0.006380199	0.002502133
Sep	0.507757469	0.33191237	0.078436221	0.042222099	0.039671838

Sheet 6

Periods	Fit & healthy S1	Average S2	Heavy S3	Overweight S4	Obese S5
Oct	0.377452818	0.41807274	0.128733908	0.060367454	0.015373078
Nov	0.316966965	0.39597085	0.207108191	0.052808746	0.027145248
Dec	0.13726404	0.18035456	0.310157848	0.242436697	0.129786857
Jan	0.037248742	0.05621538	0.181601248	0.412939238	0.311995389
Feb	0.00464124	0.01189916	0.02430642	0.301814608	0.657338571
Mar	0.005258444	0.00563418	0.030224872	0.377607944	0.581274564
Apr	0.006246519	0.01493834	0.042404487	0.282459516	0.653951139
May	0.006249386	0.01538753	0.041328186	0.283955351	0.653079546
Jun	0.013296003	0.01634254	0.087822954	0.362037697	0.520500802
Jul	0.117679145	0.20869003	0.085164054	0.186920577	0.401546192
Aug	0.159328664	0.26062023	0.07828695	0.159450671	0.342313484
Sep	0.311637788	0.33093181	0.180528273	0.098079046	0.078823081

Sheet 9

Periods	Fit & healthy S1	Average S2	Heavy S3	Overweight S4	Obese S5
Oct	0.258266819	0.38141391	0.234891676	0.078677309	0.046750285
Nov	0.123967854	0.22898038	0.418760005	0.169316923	0.058974839
Dec	0.083710421	0.17734645	0.443200276	0.216891067	0.078851785
Jan	0.107665472	0.15186092	0.173021652	0.256290172	0.31116178
Feb	0.008331034	0.01727052	0.028980142	0.299127599	0.646290701
Mar	0.002557787	0.00544969	0.014054335	0.283153259	0.694784934
Apr	0.020037686	0.03315056	0.198351612	0.398869512	0.349590632
May	0.037240875	0.06013374	0.240523773	0.356314294	0.305787316
Jun	0.044350804	0.0702936	0.247687649	0.34506411	0.292603835
Jul	0.147551005	0.25227566	0.098840799	0.182315243	0.319017297
Aug	0.480434652	0.38456904	0.072491877	0.027460535	0.035043891
Sep	0.558303288	0.38515814	0.039340853	0.008870455	0.00832726

Sheet 10

Periods	Fit & healthy S1	Average S2	Heavy S3	Overweight S4	Obese S5
Oct	0.112001187	0.220540968	0.407456856	0.191069574	0.068931415
Nov	0.208673082	0.33697915	0.285347502	0.10488079	0.064119476
Dec	0.102486957	0.148442219	0.297932558	0.281980705	0.169157561
Jan	0.018099319	0.021700837	0.073838014	0.39022667	0.496135159
Feb	0.00700571	0.008048679	0.038075923	0.385204024	0.561665664
Mar	0.002550095	0.005640041	0.014898735	0.28835845	0.688552679
Apr	0.005384421	0.01333424	0.039770995	0.284443131	0.657067212
May	0.083271011	0.102737807	0.186504234	0.257348012	0.370138936
Jun	0.052293541	0.077265461	0.239618159	0.342151805	0.288671034
Jul	0.446678424	0.379880353	0.097875508	0.036039438	0.039526277
Aug	0.303884132	0.424653352	0.070187691	0.082272437	0.119002388
Sep	0.393369968	0.289672766	0.112005403	0.096046584	0.108905279

Average

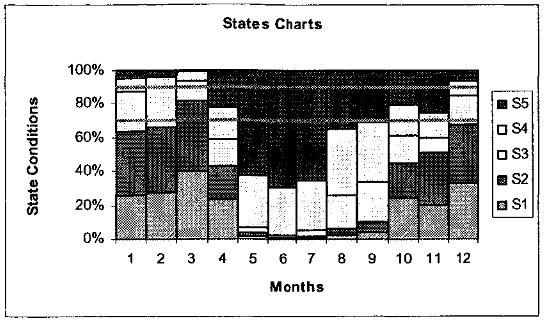
Periods	Fit & healthy S1	Average S2	Heavy S3	Overweight S4	Obese S5
1	0.194022529	0.278114349	0.261545318	0.171137448	0.095180356
2	0.241702423	0.299563789	0.217894473	0.148138824	0.092700492
3	0.215694948	0.302022668	0.233203141	0.150677887	0.098401357
4	0.088698148	0.080250729	0.098223238	0.31528647	0.417541415
5	0.060369976	0.048948613	0.058133292	0.345737278	0.486810842
6	0.032810868	0.033221018	0.07446045	0.386441895	0.47306577
7	0.03072497	0.04457523	0.155138996	0.329537668	0.440023136
8	0.052040121	0.061555283	0.10586755	0.290003429	0.490533617
9	0.034042521	0.052253052	0.187243287	0.348197073	0.378264068
10	0.348774558	0.29444279	0.117637638	0.103771153	0.135373862
11	0.412509633	0.348598831	0.099362565	0.064005077	0.075523894
12	0.516305822	0.360231517	0.068535596	0.02967311	0.025253954

Figure B1: The tables of the state transitions for the experiment I: No-Policy

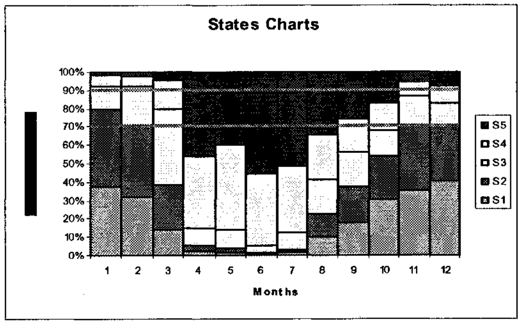
B.1.1 Graphs of the Experiment I: No-Policy Intervention

The graphs of the ten state transitions trials and their average for the No-policy intervention are illustrated in the figure 61:

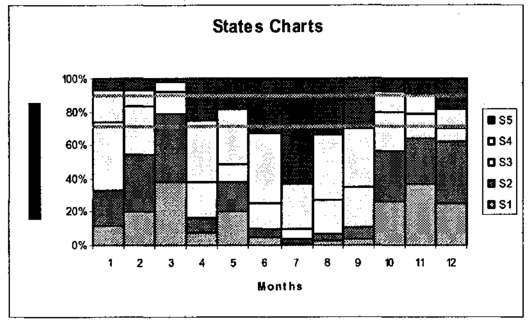
Trial # 1:



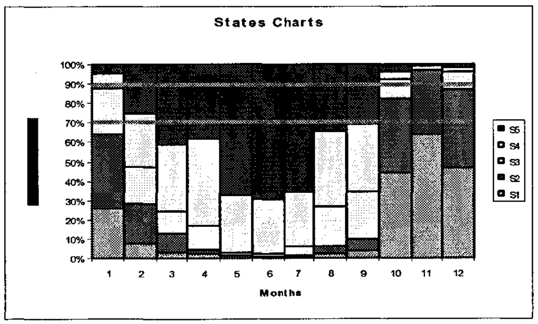
Trial # 2:



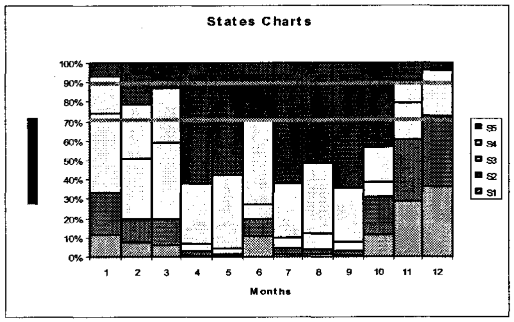
Trial # 3:



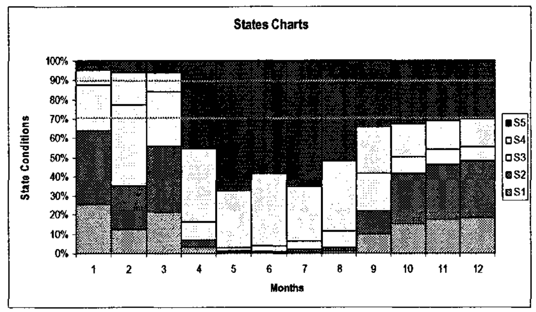
Trial # 4:



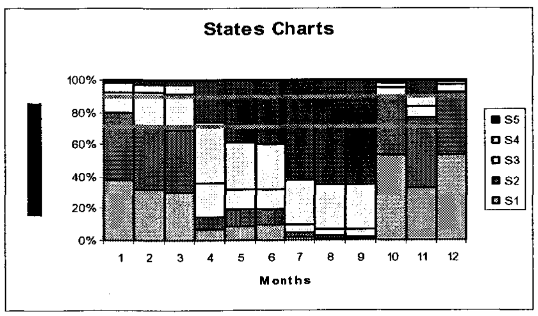
Trial # 5:



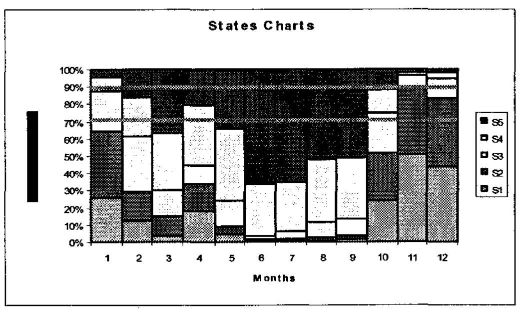
Trial # 6:



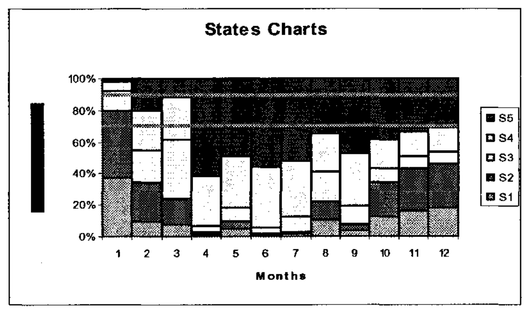
Trial # 7:



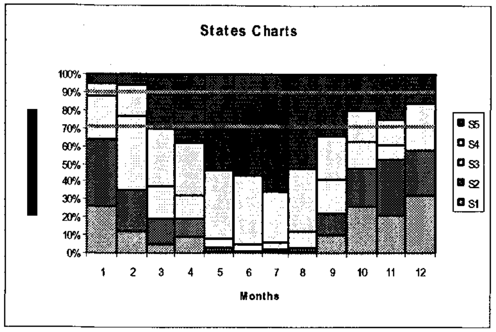
Trial # 8:



Trial # 9:



Trial # 10:



No-Policy Intervention

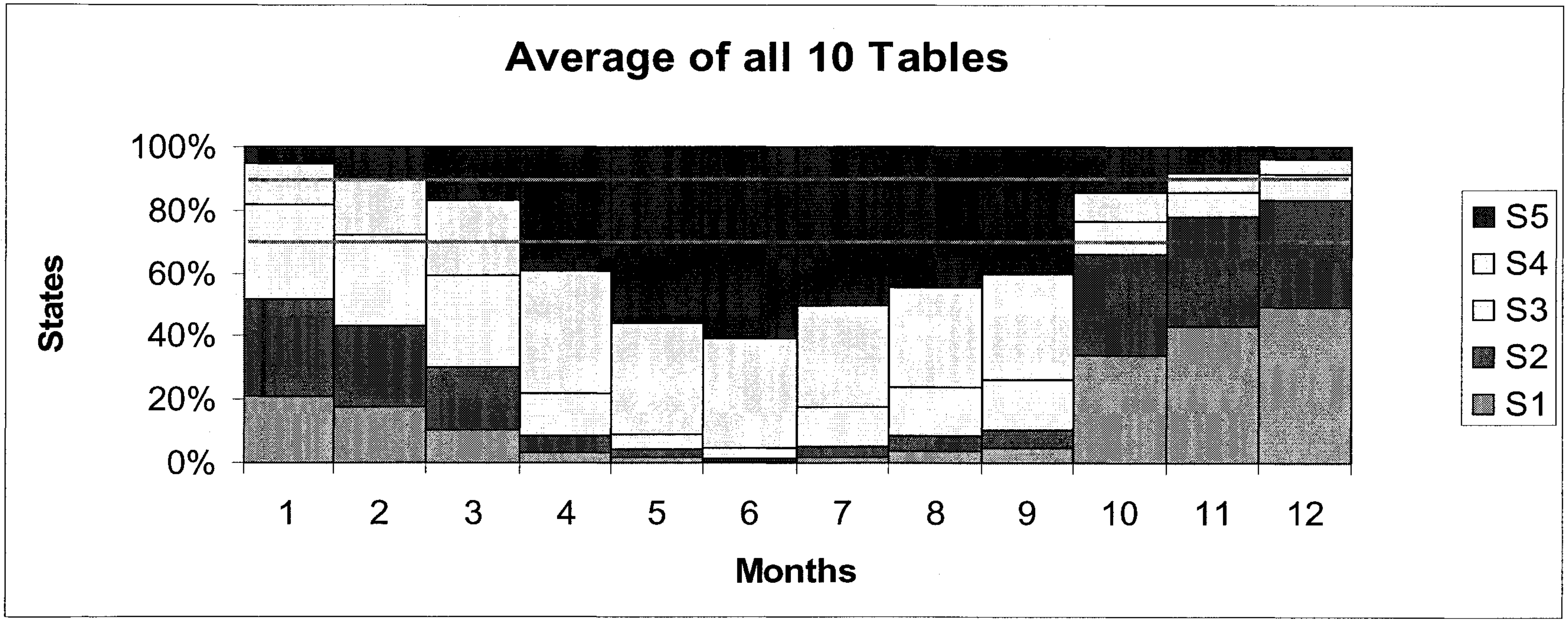


Figure B2: The graphs of the state transitions for the Experiment I: No-Policy

B.2 Experiment II: Low-Policy Intervention

The following figure illustrates the final annual probability state transitions of ten trials for the Experiment II, Low-policy intervention:

Sheet 1

0	Fit & healthy	Average	Heavy	Overweight	Obese
Periods	S1	S2	S3	S4	S5
Oct	0.104426003	0.154218534	0.284923928	0.286307054	0.170124481
Nov	0.06929689	0.110826921	0.280705533	0.283205807	0.255964849
Dec	0.051746958	0.089103769	0.248385299	0.341339054	0.26942492
Jan	0.092283805	0.116459701	0.148628836	0.273481091	0.369146567
Feb	0.009296567	0.019286342	0.033819268	0.274574743	0.663023079
Mar	0.003302348	0.007319279	0.018815934	0.270722927	0.699839511
Apr	0.027976594	0.05208671	0.242760149	0.384963193	0.292213355
May	0.026347785	0.031693021	0.115445489	0.344332299	0.482181405
Jun	0.026997735	0.034757354	0.129917156	0.36081308	0.447514674
Jul	0.48745268	0.374256636	0.051501696	0.03529775	0.051491239
Aug	0.643162975	0.331943402	0.016824495	0.005582572	0.002486556
Sep	0.581113679	0.379069301	0.029555232	0.005270753	0.004991034

Sheet 2

0	Fit & healthy	Average	Heavy	Overweight	Obese
Periods	S1	S2	S3	S4	S5
Oct	0.258266819	0.381413911	0.234891676	0.078677309	0.046750285
Nov	0.276730116	0.383360069	0.233696682	0.067493148	0.038719986
Dec	0.283040489	0.385266471	0.231590828	0.064211736	0.035890477
Jan	0.356107689	0.244041883	0.110405703	0.193043612	0.096401112
Feb	0.019705912	0.031017887	0.039639804	0.309549975	0.600086422
Mar	0.016999495	0.024222568	0.115600148	0.429233673	0.413944116
Apr	0.136327545	0.176286819	0.2270151	0.205312568	0.255057967
May	0.022754523	0.048436656	0.061402842	0.273432128	0.593973851
Jun	0.039541527	0.067276893	0.256477899	0.363079187	0.273624494
Jul	0.148091724	0.253605091	0.100716986	0.183353669	0.31423253
Aug	0.365640946	0.222918378	0.081921329	0.136073595	0.193445752
Sep	0.362704956	0.351211479	0.157443144	0.074287047	0.054353373

Sheet 4

	Fit & healthy	Average	Heavy	Overweight	Obese
Periods	S1	S2	S3	S4	S5
1	0.104426003	0.154218534	0.284923928	0.286307054	0.170124481
2	0.06929689	0.110826921	0.280705533	0.283205807	0.255964849
3	0.051746958	0.089103769	0.248385299	0.341339054	0.26942492
4	0.006719944	0.01696078	0.032468669	0.29871616	0.645134447
5	0.131790982	0.110997522	0.096970767	0.391217547	0.269023183
6	0.008517936	0.01542313	0.025912249	0.30273726	0.647409425
7	0.009353756	0.025144385	0.055673636	0.303715924	0.6061123
8	0.021254524	0.02839756	0.118636395	0.370145079	0.46156644
9	0.026573495	0.034475137	0.130804015	0.360470539	0.447676814
10	0.271063499	0.208259399	0.086073477	0.176768932	0.257834692
11	0.50166635	0.379910229	0.065183242	0.023684632	0.029555548
12	0.645271898	0.331350803	0.01634678	0.005019442	0.002011077

Sheet 5

	Fit & healthy	Average	Heavy	Overweight	Obese
Periods	S1	S2	S3	S4	S5
1	0.377452818	0.418072741	0.128733908	0.060367454	0.015373078
2	0.436928867	0.409374905	0.107059518	0.038217467	0.008419244
3	0.166866597	0.264778059	0.398718304	0.131024273	0.038612767
4	0.013442006	0.03089724	0.047530855	0.314673315	0.593456584
5	0.008447478	0.009480569	0.046014491	0.362267714	0.573789748
6	0.003326706	0.007755524	0.020189019	0.27644598	0.692282771
7	0.008364072	0.023293992	0.054077334	0.304739113	0.609525488
8	0.232633133	0.234060587	0.164404483	0.240388708	0.128513088
9	0.090587815	0.118957825	0.260702447	0.291216619	0.238535295
10	0.486615216	0.390066744	0.072220685	0.029938268	0.021159087
11	0.430233275	0.394684622	0.119403433	0.036148337	0.019530333
12	0.449208636	0.315592345	0.106541562	0.07156307	0.057094387

Sheet 7

	Fit & healthy	Average	Heavy	Overweight	Obese
Periods	S1	S2	S3	S4	S5
1	0.377452818	0.418072741	0.128733908	0.060367454	0.015373078
2	0.153764176	0.256119778	0.401881887	0.143461395	0.044772764
3	0.229570104	0.351250841	0.276210729	0.090462598	0.052505728
4	0.180675984	0.177031954	0.168119421	0.217393274	0.256779367
5	0.027396033	0.025042798	0.07728028	0.374079264	0.496201624
6	0.009916722	0.011266943	0.051548416	0.36589228	0.56137564
7	0.033662765	0.059676052	0.257075044	0.369806304	0.279779835
8	0.027881723	0.033381254	0.117219664	0.343066614	0.478450744
9	0.027412357	0.03516228	0.130367527	0.360352267	0.446705569
10	0.311658422	0.318814626	0.1316718	0.126163414	0.111691738
11	0.522846896	0.385842493	0.057265795	0.016833218	0.017211598
12	0.439670608	0.398248526	0.11206823	0.032299899	0.017712737

Sheet 8

	Fit & healthy	Average	Heavy	Overweight	Obese
Periods	S1	S2	S3	S4	S5
1	0.258266819	0.381413911	0.234891676	0.078677309	0.046750285
2	0.276730116	0.383360069	0.233696682	0.067493148	0.038719986
3	0.125017919	0.170170751	0.306878392	0.255258742	0.142674196
4	0.268014557	0.224000236	0.124566058	0.248953469	0.134465681
5	0.017927	0.029524231	0.041675222	0.30303427	0.607839276
6	0.016575595	0.023928123	0.115066536	0.42941819	0.415011556
7	0.013092365	0.033890819	0.06559607	0.297000833	0.590419914
8	0.244253485	0.241245668	0.161472799	0.230174026	0.122854022
9	0.407087645	0.299158047	0.107145963	0.11835441	0.068253935
10	0.538721794	0.382777022	0.051008181	0.0139209	0.013572103
11	0.567985509	0.383717889	0.034961546	0.007011179	0.006323876
12	0.452178346	0.403105711	0.10283763	0.026978822	0.014899491

Sheet 3

Periods	Fit & healthy S1	Average S2	Heavy S3	Overweight S4	Obese S5
1	0.258266819	0.38141391	0.234891676	0.078677309	0.046750285
2	0.397582277	0.41308434	0.125908313	0.050908415	0.012516656
3	0.442553479	0.40759455	0.105522174	0.036465228	0.00786457
4	0.085489	0.08891592	0.213239524	0.362724405	0.249631153
5	0.225794403	0.18824098	0.114780486	0.2990918	0.172092334
6	0.015185011	0.02541228	0.037555854	0.301509324	0.620337532
7	0.034422416	0.06010555	0.251376663	0.372581433	0.28151394
8	0.280141509	0.25070238	0.147071877	0.201526526	0.120557711
9	0.041154465	0.07904771	0.082815145	0.251248138	0.545734538
10	0.318217856	0.31715871	0.120400953	0.123970106	0.120252375
11	0.523555551	0.38541357	0.056515449	0.016819504	0.017695921
12	0.329872645	0.44808315	0.062969084	0.064891049	0.094184072

Sheet 6

Periods	Fit & healthy S1	Average S2	Heavy S3	Overweight S4	Obese S5
1	0.258266819	0.38141391	0.234891676	0.078677309	0.046750285
2	0.124886174	0.17300745	0.316396547	0.22844354	0.157266287
3	0.216571327	0.33735415	0.274143958	0.098408302	0.07352226
4	0.0163929	0.03244844	0.046731609	0.310499748	0.593927305
5	0.008741388	0.00964702	0.046186241	0.361831403	0.573593948
6	0.003340985	0.00777833	0.020210546	0.276426862	0.692243279
7	0.017231845	0.02399372	0.111388446	0.376600694	0.470785291
8	0.012574803	0.03291498	0.063952074	0.297887687	0.592670458
9	0.036124562	0.06352928	0.256422153	0.366645102	0.277278904
10	0.557567087	0.35891333	0.047820823	0.024447763	0.011250999
11	0.651194254	0.32789477	0.015001939	0.004259841	0.0016492
12	0.660828423	0.32245646	0.012409595	0.00306123	0.001244289

Sheet 9

Periods	Fit & healthy S1	Average S2	Heavy S3	Overweight S4	Obese S5
1	0.258266819	0.38141391	0.234891676	0.078677309	0.046750285
2	0.123967854	0.22898038	0.418760005	0.169316923	0.058974839
3	0.083710421	0.17734645	0.443200276	0.216891067	0.078851785
4	0.030801973	0.05792778	0.197998787	0.410602948	0.302668516
5	0.022788706	0.04083358	0.168500083	0.408861433	0.359016198
6	0.011046606	0.01492909	0.064535031	0.368340525	0.541148746
7	0.021945158	0.0290635	0.12209057	0.368222264	0.458678504
8	0.137535834	0.1783445	0.224322613	0.205108497	0.254688554
9	0.022862788	0.04857295	0.061395392	0.273345326	0.593823545
10	0.305352946	0.31640314	0.117871511	0.13098113	0.129391277
11	0.36533893	0.36049749	0.161428616	0.068361042	0.044373921
12	0.39321444	0.37810499	0.149559572	0.052625055	0.02649594

Sheet 10

Periods	Fit & healthy S1	Average S2	Heavy S3	Overweight S4	Obese S5
1	0.258266819	0.381413911	0.234891676	0.078677309	0.046750285
2	0.075071571	0.207996464	0.190192279	0.274643942	0.252095744
3	0.072563459	0.16695866	0.383421906	0.253597539	0.123458435
4	0.233917434	0.230209977	0.135598483	0.260847669	0.139426436
5	0.034375616	0.029337125	0.085610471	0.376957718	0.473719071
6	0.020102647	0.030077753	0.133150742	0.42400339	0.392665468
7	0.028093955	0.036151097	0.135313962	0.357157693	0.443283294
8	0.014225006	0.036466325	0.066318209	0.296014993	0.586975467
9	0.246723316	0.242465072	0.160773568	0.228260088	0.121777956
10	0.504323628	0.383493863	0.069097845	0.021524434	0.021560231
11	0.323598539	0.442655823	0.065070509	0.069372613	0.099302517
12	0.625107235	0.342184632	0.020927043	0.007979233	0.003801857

Average

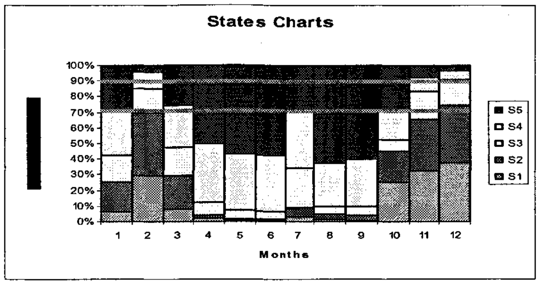
Periods	Fit & healthy S1	Average S2	Heavy S3	Overweight S4	Obese S5
1	0.251335855	0.343306602	0.223666573	0.116541287	0.065149683
2	0.200425493	0.26769373	0.258900298	0.160638959	0.11234152
3	0.172338771	0.243892747	0.291645716	0.182899759	0.109223006
4	0.128384529	0.12188939	0.122528795	0.289093569	0.338103717
5	0.050626409	0.049340805	0.075047711	0.346146587	0.478838488
6	0.010831405	0.016811302	0.060258448	0.344473041	0.567625804
7	0.033047047	0.051969265	0.152236697	0.334010002	0.428736989
8	0.101960233	0.111564293	0.124024645	0.280207656	0.382243174
9	0.096506571	0.102340255	0.157682126	0.297378476	0.346092572
10	0.392906485	0.330374855	0.084838396	0.086636637	0.105243627
11	0.489522323	0.361547867	0.067357635	0.038414653	0.043157522
12	0.493917087	0.36694074	0.077065787	0.03439756	0.027678826

Figure B3: The tables of the state transitions for the experiment II: Low-Policy

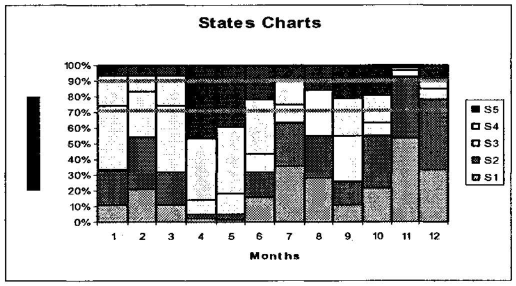
B.2.1 Graphs of the Experiment II: Low-Policy Intervention

The graphs of the ten state transitions trials and their average for the Low-policy intervention are illustrated in the figure 63:

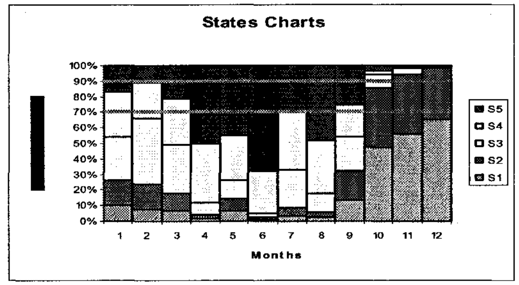
Trial # 1:



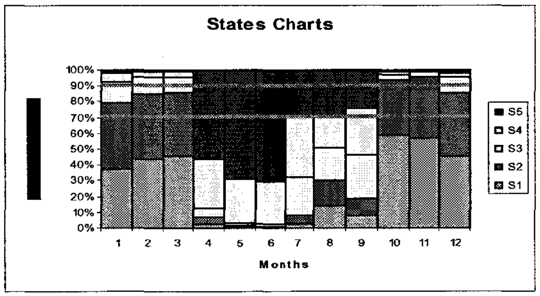
Trial # 2:



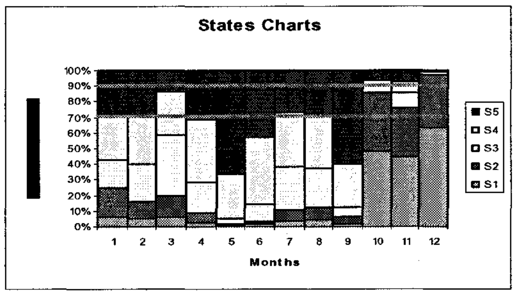
Trial # 3:



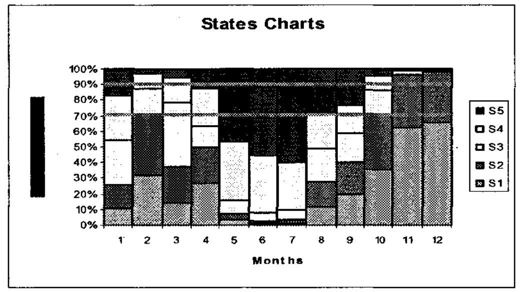
Trial # 4:



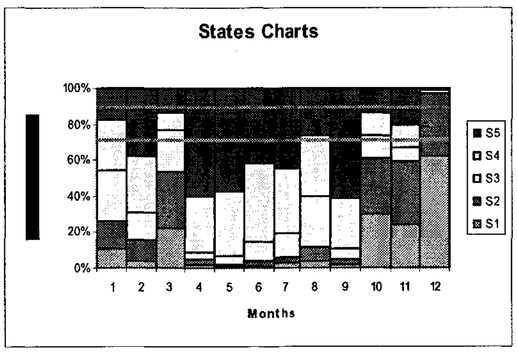
Trial # 5:



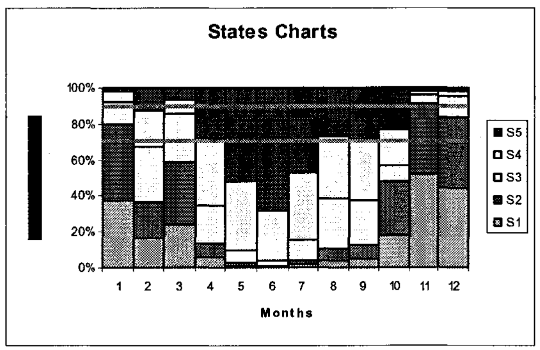
Trial # 6:



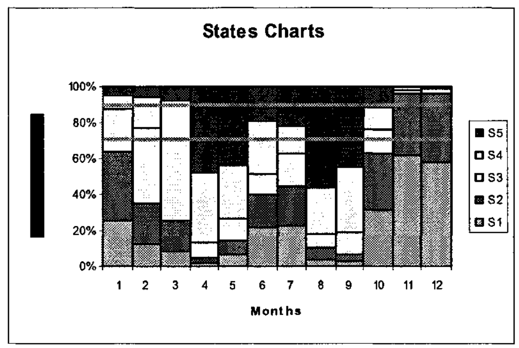
Trial # 7:



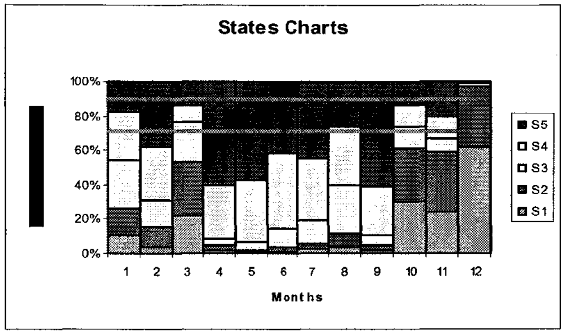
Trial # 8:



Trial # 9:



Trial # 10:



Low-Policy Intervention

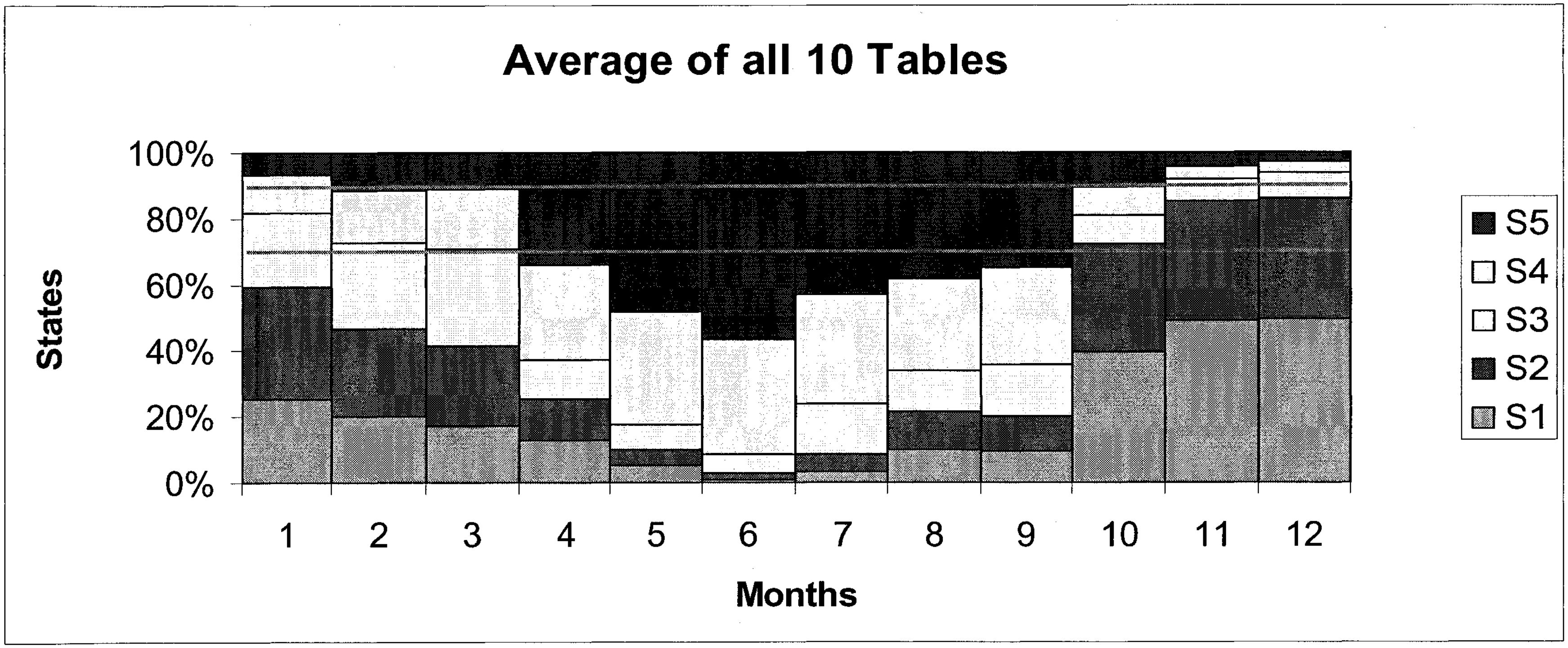


Figure B4: The graphs of the state transitions for the Experiment II: Low-Policy

B.3 Experiment III: Moderate-Policy Intervention

The following figure illustrates the final annual probability state transitions of ten trials for the experiment III, Moderate-policy intervention:

Sheet 1

0 Periods	Fit & healthy S1	Average S2	Heavy S3	Overweight S4	Obese S5
Oct	0.377452818	0.418072741	0.128733908	0.060367454	0.015373078
Nov	0.316966965	0.395970849	0.207108191	0.052808746	0.027145248
Dec	0.138488183	0.242617317	0.417231846	0.1521948	0.049467853
Jan	0.264086809	0.241358628	0.127655328	0.243072169	0.123827065
Feb	0.037482123	0.031139084	0.088134341	0.375743903	0.467500549
Mar	0.020737897	0.030800889	0.13458525	0.422829329	0.391046634
Apr	0.014054818	0.036130286	0.067361922	0.295586276	0.586866698
May	0.246508333	0.242550554	0.160877605	0.228269078	0.12179443
Jun	0.252058229	0.246732851	0.176092492	0.138644921	0.186471507
Jul	0.382610127	0.371279082	0.136929266	0.074646033	0.034535492
Aug	0.541344459	0.387373771	0.049128769	0.01204791	0.01010509
Sep	0.650383686	0.329183774	0.014807848	0.004071219	0.001553472

Sheet 2

0 Periods	Fit & healthy S1	Average S2	Heavy S3	Overweight S4	Obese S5
Oct	0.258266819	0.381413911	0.234891676	0.078677309	0.046750285
Nov	0.276730116	0.383360069	0.233696682	0.067493148	0.038719986
Dec	0.403983767	0.412418204	0.123956119	0.04811595	0.01152596
Jan	0.403553428	0.242704927	0.099676997	0.170660535	0.083404113
Feb	0.021677472	0.033101633	0.040716903	0.310040679	0.594463313
Mar	0.00917994	0.009750162	0.04595982	0.361527514	0.573582563
Apr	0.113639464	0.151612863	0.220365779	0.228975548	0.285406347
May	0.028302564	0.064102336	0.081791562	0.28366542	0.542138117
Jun	0.028049531	0.035067903	0.12574284	0.362420558	0.448719168
Jul	0.487824115	0.373998417	0.051204243	0.035339888	0.051633337
Aug	0.454389378	0.312646542	0.095036212	0.06759774	0.070330127
Sep	0.406436847	0.378407654	0.135166284	0.049813501	0.030175714

Sheet 4

Periods	Fit & healthy S1	Average S2	Heavy S3	Overweight S4	Obese S5
1	0.104426003	0.154218534	0.284923928	0.286307054	0.170124481
2	0.324228134	0.388904962	0.164171565	0.092754961	0.029940379
3	0.085665966	0.222079444	0.187403485	0.268314705	0.2365364
4	0.011685905	0.025313901	0.0424979	0.275012537	0.645489757
5	0.015064167	0.022455074	0.111505826	0.430408188	0.420566745
6	0.064985322	0.084003837	0.13090642	0.288860797	0.431243624
7	0.17391288	0.206100118	0.214355416	0.182554557	0.223077028
8	0.096244072	0.137389858	0.306986299	0.269972882	0.189406889
9	0.020829016	0.046762638	0.064008449	0.274000385	0.594399511
10	0.304406574	0.316510107	0.118416875	0.131184569	0.129481876
11	0.2396238	0.354809496	0.079544031	0.120322046	0.205700627
12	0.603123971	0.321294538	0.0365599	0.016836562	0.022185028

Sheet 5

Periods	Fit & healthy S1	Average S2	Heavy S3	Overweight S4	Obese S5
1	0.258266819	0.381413911	0.234891676	0.078677309	0.046750285
2	0.276730116	0.383360069	0.233696682	0.067493148	0.038719986
3	0.128380164	0.232996454	0.420175483	0.163099189	0.05534871
4	0.131420623	0.163505765	0.175042665	0.241616375	0.288414573
5	0.012297582	0.02453593	0.039669023	0.273400009	0.650097456
6	0.003536559	0.007824217	0.019470689	0.27082823	0.698340305
7	0.099510024	0.138747163	0.214898465	0.243027979	0.303816369
8	0.026245995	0.060293044	0.079813629	0.285088349	0.548558982
9	0.013497809	0.033954013	0.061708919	0.298678424	0.592160834
10	0.476794138	0.377097575	0.04717353	0.037858398	0.061076359
11	0.449275823	0.310333743	0.095477317	0.069818115	0.075095002
12	0.635636685	0.33356662	0.020071239	0.007489562	0.003235894

Sheet 7

Periods	Fit & healthy S1	Average S2	Heavy S3	Overweight S4	Obese S5
1	0.258266819	0.381413911	0.234891676	0.078677309	0.046750285
2	0.123967854	0.228980379	0.418760005	0.169316923	0.058974839
3	0.334080655	0.398122597	0.165822363	0.081149293	0.020825092
4	0.022470644	0.038195794	0.049652468	0.312370304	0.577310791
5	0.004329887	0.009356782	0.021627459	0.273474943	0.691210929
6	0.006410543	0.007073771	0.038970718	0.360910309	0.586634657
7	0.019601319	0.02638543	0.117687334	0.372114324	0.464211593
8	0.02615722	0.034088643	0.13045064	0.360870398	0.448433099
9	0.142008578	0.182587676	0.223936194	0.201542801	0.249924751
10	0.648903131	0.306482236	0.022499582	0.014329223	0.007785828
11	0.352023014	0.458581776	0.055623618	0.052859663	0.080911929
12	0.40179947	0.386407505	0.132339734	0.04768017	0.03177312

Sheet 8

Periods	Fit & healthy S1	Average S2	Heavy S3	Overweight S4	Obese S5
1	0.112001187	0.220540968	0.407456856	0.191069574	0.068931415
2	0.075459209	0.121856542	0.30955737	0.284448097	0.208678782
3	0.245081086	0.349406185	0.227405049	0.082395592	0.095712088
4	0.05860145	0.073022139	0.203841079	0.383593869	0.280941464
5	0.015878331	0.019408722	0.074691632	0.364304616	0.525716699
6	0.003919813	0.009365765	0.022518211	0.277600525	0.686595687
7	0.028723271	0.053099765	0.24422123	0.383187101	0.290768633
8	0.05250481	0.090503619	0.299121437	0.318344232	0.239525902
9	0.325448421	0.30522532	0.149482232	0.144023284	0.075820743
10	0.619384294	0.340801191	0.025661702	0.010103313	0.0040495
11	0.459175342	0.402536151	0.098475186	0.025479427	0.014333894
12	0.641210395	0.334166823	0.017549124	0.005254365	0.001819293

Sheet 3

Periods	Fit & healthy S1	Average S2	Heavy S3	Overweight S4	Obese S5
1	0.258266819	0.38141391	0.234891676	0.078677309	0.046750285
2	0.123967854	0.22898038	0.418760005	0.169316923	0.058974839
3	0.083710421	0.17734645	0.443200276	0.216891067	0.078851785
4	0.008794268	0.02480843	0.042397958	0.314012145	0.6099872
5	0.003507524	0.00797931	0.020090817	0.273330628	0.695091718
6	0.012219668	0.01799071	0.100229116	0.43747903	0.432081477
7	0.130255459	0.1699914	0.227048209	0.210647757	0.262057178
8	0.230197516	0.25662475	0.208771012	0.139373562	0.165033155
9	0.063763123	0.0640184	0.134194367	0.317336582	0.420687529
10	0.290082498	0.2102383	0.086296175	0.168469847	0.244913177
11	0.690424605	0.27421524	0.016533215	0.011845226	0.006981717
12	0.510978294	0.32841313	0.076292437	0.042746903	0.041569235

Sheet 6

Periods	Fit & healthy S1	Average S2	Heavy S3	Overweight S4	Obese S5
1	0.258266819	0.38141391	0.234891676	0.078677309	0.046750285
2	0.397582277	0.41308434	0.125908313	0.050908415	0.012516656
3	0.322603977	0.3961604	0.205123973	0.050631826	0.025479825
4	0.022035939	0.03863834	0.05081249	0.312047183	0.576466049
5	0.018056348	0.02612641	0.12075338	0.42629271	0.408771155
6	0.009720339	0.012556	0.057498356	0.369768221	0.55045709
7	0.021328224	0.02834475	0.121012833	0.369220864	0.460093333
8	0.041594861	0.07201209	0.272721354	0.349859029	0.263812668
9	0.020126003	0.05105252	0.079142365	0.285727465	0.563951649
10	0.306390609	0.31741388	0.121275981	0.12956286	0.125356667
11	0.616750721	0.34215356	0.02550183	0.010727737	0.004866156
12	0.458605646	0.40237825	0.098779405	0.025699086	0.014537611

Sheet 9

Periods	Fit & healthy S1	Average S2	Heavy S3	Overweight S4	Obese S5
1	0.112001187	0.22054097	0.407456856	0.191069574	0.068931415
2	0.080113833	0.17249752	0.438202796	0.225488842	0.083697013
3	0.036039617	0.12204254	0.170149303	0.335527397	0.336241139
4	0.015458415	0.01888935	0.073011677	0.359459306	0.533181247
5	0.003875303	0.00924594	0.022313555	0.277243312	0.687321889
6	0.002871766	0.0063726	0.017578929	0.270539319	0.702637384
7	0.09821971	0.13752594	0.2148807	0.24412099	0.305252657
8	0.073118354	0.11215281	0.297926112	0.298626015	0.218176708
9	0.0489707	0.05928158	0.16445959	0.328052979	0.399235154
10	0.324262318	0.31917775	0.136225604	0.118466268	0.101868057
11	0.619564692	0.34116731	0.024899725	0.010059421	0.004308851
12	0.578013963	0.38000608	0.030940899	0.005718267	0.005320791

Sheet 10

Periods	Fit & healthy S1	Average S2	Heavy S3	Overweight S4	Obese S5
1	0.377452818	0.418072741	0.128733908	0.060367454	0.015373078
2	0.099868275	0.249520803	0.195763662	0.249580508	0.205266752
3	0.272941532	0.377561511	0.194916376	0.070575847	0.084004735
4	0.019258776	0.034552035	0.046896551	0.308495207	0.59079743
5	0.157141886	0.128348346	0.100900926	0.36540755	0.248201292
6	0.012639127	0.02257299	0.036193812	0.279247021	0.64934705
7	0.032935702	0.058473382	0.248917898	0.375547302	0.284125716
8	0.036443299	0.046748222	0.151735084	0.34195901	0.423114385
9	0.152792135	0.192898976	0.223025837	0.192893216	0.238389836
10	0.55511044	0.344065669	0.050314838	0.022397941	0.028111112
11	0.567559647	0.381640303	0.03564708	0.007710995	0.007441975
12	0.572567821	0.382902388	0.03270668	0.00617909	0.005644022

Average

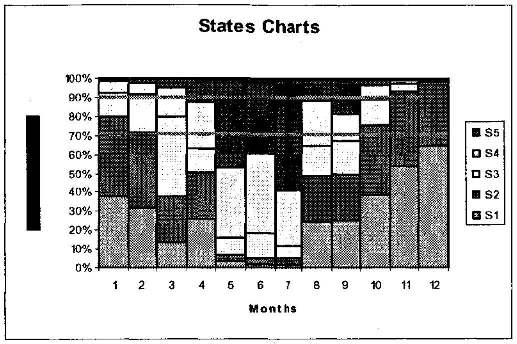
Periods	Fit & healthy S1	Average S2	Heavy S3	Overweight S4	Obese S5
1	0.237466811	0.333851551	0.253176384	0.118256766	0.057248489
2	0.209561463	0.296651591	0.274562527	0.142960971	0.076263448
3	0.205097537	0.293075111	0.255538427	0.146889567	0.099399359
4	0.095736626	0.090098931	0.091148511	0.292033963	0.430981969
5	0.028931062	0.031169723	0.064040386	0.336964654	0.538894174
6	0.014622097	0.020831094	0.060391132	0.333959029	0.570196647
7	0.073218087	0.100641109	0.189074978	0.29049827	0.346567555
8	0.085731702	0.111646593	0.199019473	0.287602798	0.315999434
9	0.106754354	0.121758187	0.140179329	0.254332062	0.376976068
10	0.439576824	0.327706421	0.07959978	0.074235834	0.0788114
11	0.499013148	0.356545789	0.057586698	0.038846828	0.048007537
12	0.545875678	0.357672676	0.059521355	0.021148873	0.015781418

Figure B5: The tables of the state transitions for the Experiment III: Moderate-Policy

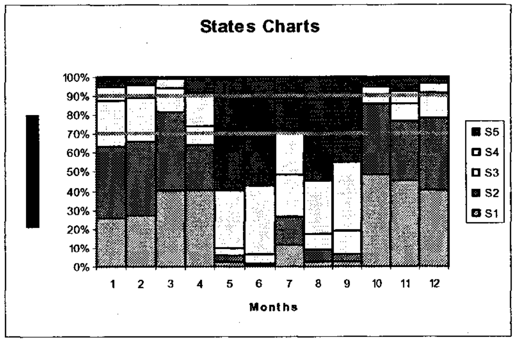
B.3.1 Graphs of the Experiment III: Moderate-Policy Intervention

The graphs of the ten state transitions trials and their average for the Moderate-policy intervention are illustrated in the figure 65:

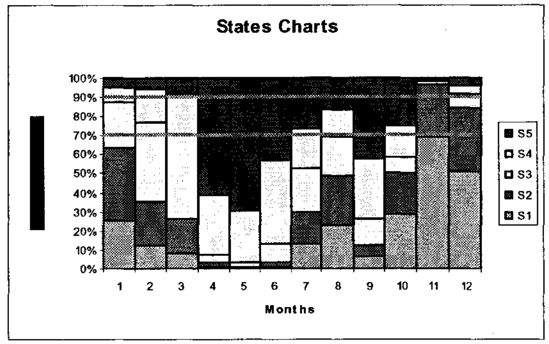
Trial # 1:



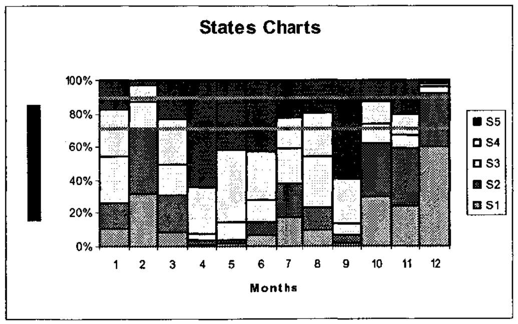
Trial # 2:



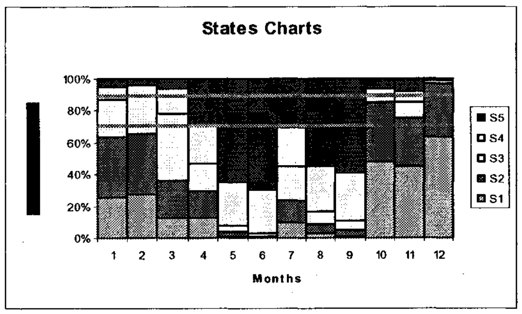
Trial # 3:



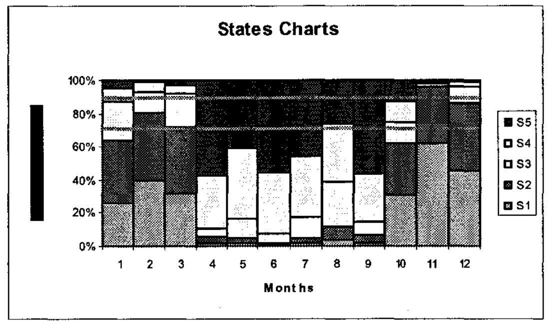
Trial # 4:



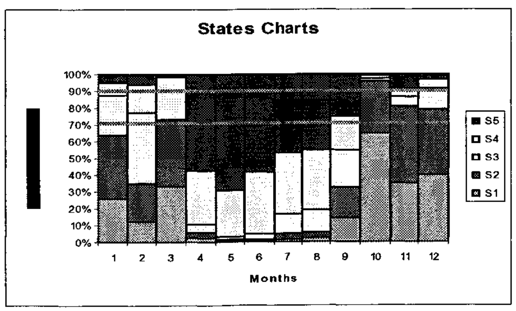
Trial # 5:



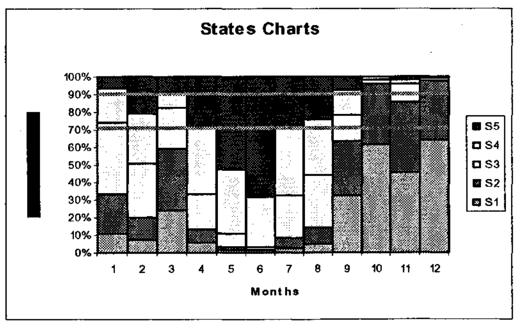
Trial # 6:



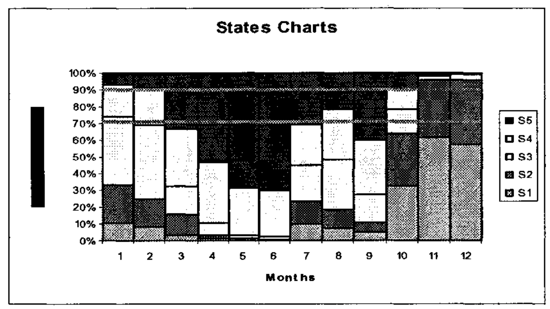
Trial # 7:



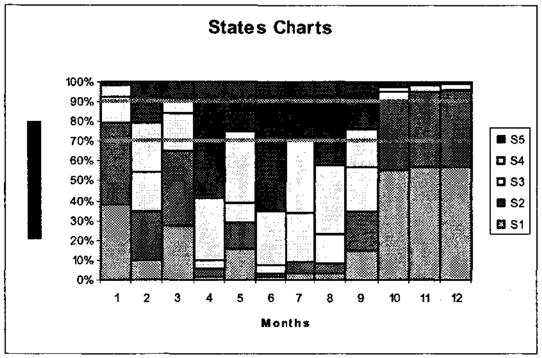
Trial # 8:



Trial # 9:



Trial # 10:



Moderate-Policy Intervention

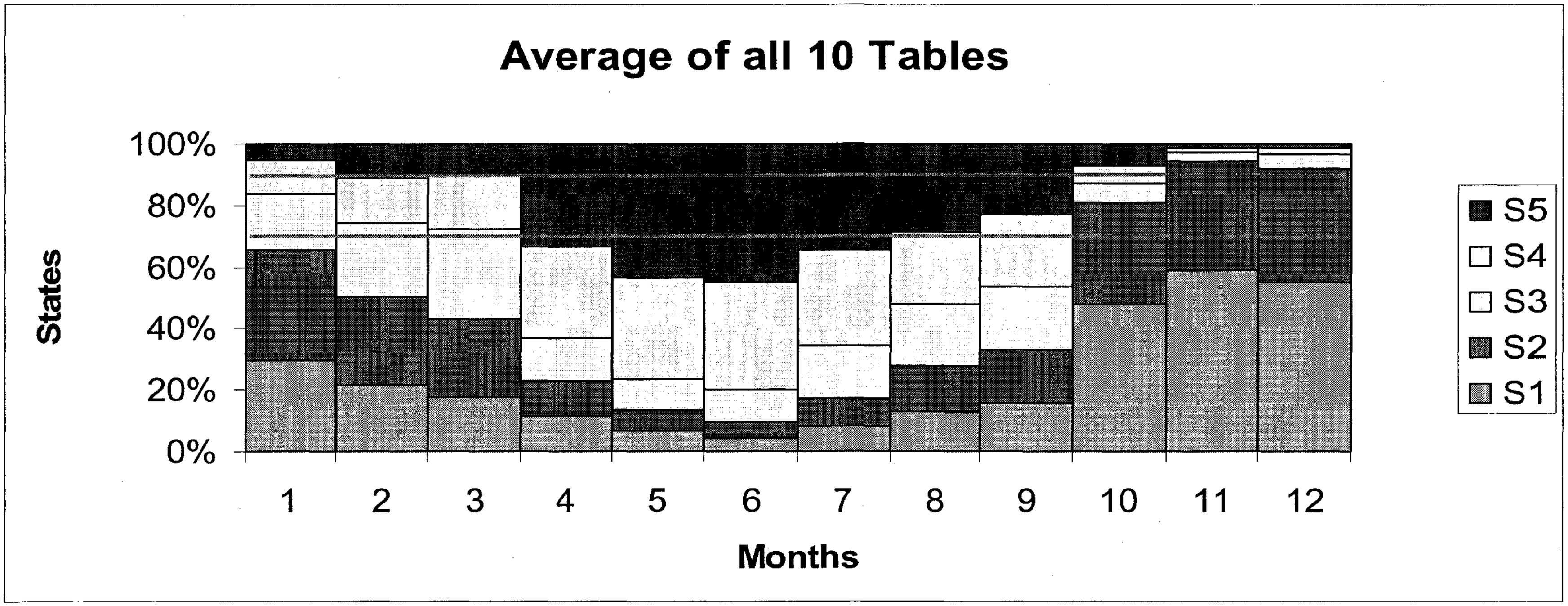


Figure B6: The graphs of the state transitions for the Experiment III: Moderate-Policy

B.4 Experiment IV: Extensive-Policy Intervention

The following figure illustrates the final annual probability state transitions of ten trials for the Experiment IV, Extensive-policy intervention:

Sheet 1

Periods	Hralthy & Fit S1	Average S2	Heavy S3	Overweight S4	Obese S5
Oct	0.112001187	0.220540968	0.407456856	0.191069574	0.068931415
Nov	0.221108617	0.356190406	0.286278568	0.081045012	0.055377397
Dec	0.276670243	0.397689002	0.237599276	0.052164595	0.035876884
Jan	0.215791123	0.195514915	0.181673887	0.1902361	0.216783975
Feb	0.059594454	0.072243575	0.20986789	0.347955908	0.310338173
Mar	0.032641673	0.051919323	0.183537185	0.419284155	0.312617664
Apr	0.224572005	0.220034355	0.190996485	0.163419427	0.200977728
May	0.139715583	0.163118087	0.300726241	0.232244935	0.164195153
Jun	0.29496573	0.272059744	0.188390967	0.114995951	0.129587608
Jul	0.526343529	0.331671228	0.053069941	0.060124759	0.028790543
Aug	0.65811848	0.260337624	0.017993881	0.036297861	0.027252153
Sep	0.726344065	0.26328813	0.004942037	0.002912259	0.002513509

Sheet 2

Periods	Hralthy & Fit S1	Average S2	Heavy S3	Overweight S4	Obese S5
Oct	0.112001187	0.220540968	0.407456856	0.191069574	0.068931415
Nov	0.089038988	0.191247382	0.461129996	0.182763246	0.075820388
Dec	0.208356321	0.348177614	0.301421436	0.084495132	0.057549497
Jan	0.188556479	0.187242348	0.185032702	0.202879057	0.236289414
Feb	0.028642538	0.026392276	0.080694488	0.37390308	0.490367619
Mar	0.010107644	0.011499901	0.05217471	0.365807807	0.560409938
Apr	0.019247974	0.040036666	0.054806543	0.287635178	0.598273639
May	0.351604076	0.273615788	0.116410046	0.165924711	0.092445379
Jun	0.14223436	0.117026932	0.1934006	0.253473948	0.293864159
Jul	0.680522729	0.284707613	0.014593739	0.014327663	0.005848255
Aug	0.787960699	0.209772587	0.001104683	0.000907907	0.000254124
Sep	0.588276749	0.389880018	0.004224341	0.009338591	0.008280301

Sheet 4

Periods	Hralthy & Fit S1	Average S2	Heavy S3	Overweight S4	Obese S5
Oct	0.112001187	0.220540968	0.407456856	0.191069574	0.068931415
Nov	0.050981247	0.164254394	0.198022654	0.280299508	0.306442197
Dec	0.041638479	0.122375324	0.115652546	0.23582472	0.484508931
Jan	0.032246954	0.046983946	0.164369932	0.43205318	0.324345987
Feb	0.014950382	0.019112589	0.071453917	0.399671909	0.494811203
Mar	0.011200819	0.013680601	0.055108019	0.408629742	0.51138082
Apr	0.040055965	0.040829331	0.113344586	0.350723902	0.455046216
May	0.371124266	0.277007428	0.11723966	0.152116811	0.082511835
Jun	0.083864677	0.137496832	0.111870235	0.235013765	0.431754491
Jul	0.570436697	0.331365419	0.040589121	0.027665263	0.029943501
Aug	0.774032191	0.221356256	0.0019711	0.001988791	0.000651663
Sep	0.798483028	0.20017791	0.000743946	0.000478195	0.000116921

Sheet 5

Periods	Hralthy & Fit S1	Average S2	Heavy S3	Overweight S4	Obese S5
Oct	0.112001187	0.220540968	0.407456856	0.191069574	0.068931415
Nov	0.086969526	0.140101779	0.33780924	0.239083161	0.196036294
Dec	0.072344119	0.160593417	0.428344319	0.231594969	0.107123176
Jan	0.009699745	0.026462803	0.046708285	0.308171202	0.608957965
Feb	0.007905343	0.009040641	0.044975264	0.362211676	0.575867077
Mar	0.004534328	0.010945205	0.023057381	0.319304658	0.642158429
Apr	0.182167841	0.194360292	0.175880009	0.193303099	0.254288759
May	0.094636386	0.084349548	0.163012233	0.30013448	0.357867353
Jun	0.093339783	0.117955209	0.268439034	0.298080293	0.222185681
Jul	0.266656913	0.31109639	0.0447426	0.160155361	0.217348736
Aug	0.50187673	0.241939172	0.051278594	0.098358441	0.106547063
Sep	0.689695109	0.281639992	0.012587381	0.008146778	0.00793074

Sheet 7

Periods	Hralthy & Fit S1	Average S2	Heavy S3	Overweight S4	Obese S5
Oct	0.377452818	0.418072741	0.128733908	0.060367454	0.015373078
Nov	0.316966965	0.395970849	0.207108191	0.052808746	0.027145248
Dec	0.0880863	0.231477459	0.199037251	0.259297721	0.222101269
Jan	0.142165498	0.15484252	0.172011567	0.215649071	0.315331344
Feb	0.321132951	0.224144275	0.113933011	0.225212176	0.115577587
Mar	0.059046286	0.044419613	0.112973612	0.369773419	0.413787071
Apr	0.026320594	0.051003776	0.06347601	0.284699991	0.574499629
May	0.20782529	0.212592148	0.177380582	0.175253016	0.226948964
Jun	0.134730187	0.158123546	0.296210252	0.239310964	0.171625051
Jul	0.294814997	0.326860087	0.039307649	0.151520624	0.187496643
Aug	0.356504796	0.335590641	0.032155208	0.101317657	0.174431698
Sep	0.381652676	0.340087562	0.027889303	0.091444519	0.15892594

Sheet 8

Periods	Hralthy & Fit S1	Average S2	Heavy S3	Overweight S4	Obese S5
Oct	0.258266819	0.381413911	0.234891676	0.078677309	0.046750285
Nov	0.124886174	0.173007452	0.316396547	0.22844354	0.157266287
Dec	0.216571327	0.337354154	0.274143958	0.098408302	0.07352226
Jan	0.190077613	0.184050011	0.180528986	0.20440842	0.24093497
Feb	0.015667444	0.029188761	0.043678924	0.271227757	0.640237113
Mar	0.005168878	0.011528902	0.023375959	0.318913712	0.641012549
Apr	0.182697828	0.194685332	0.17586845	0.192956667	0.253791723
May	0.309061353	0.275392888	0.177292423	0.108683926	0.12956941
Jun	0.359538897	0.304435264	0.17129027	0.077305845	0.087429724
Jul	0.409379452	0.365684304	0.021884034	0.094366006	0.108686204
Aug	0.594706628	0.254445973	0.031359226	0.058153039	0.061335133
Sep	0.650792421	0.247230749	0.021787983	0.041344427	0.038844419

Sheet 3

Periods	Hralthy & Fit S1	Average S2	Heavy S3	Overweight S4	Obese S5
Oct	0.104426003	0.154218534	0.284923928	0.286307054	0.170124481
Nov	0.06929689	0.110826921	0.280705533	0.283205807	0.255964849
Dec	0.177514412	0.305664403	0.284022944	0.130104483	0.102693758
Jan	0.03373329	0.034155042	0.104340733	0.375362264	0.452408671
Feb	0.076421347	0.088938571	0.129241007	0.280347394	0.425051681
Mar	0.127256371	0.129864997	0.146705374	0.267633697	0.328539561
Apr	0.275902299	0.25315011	0.179261323	0.130910509	0.160775759
May	0.154771528	0.176788076	0.308332225	0.212185024	0.147923147
Jun	0.302736571	0.277252057	0.187674018	0.109878438	0.122458916
Jul	0.530771297	0.332082521	0.051112955	0.058453722	0.027579505
Aug	0.621310306	0.326599625	0.022036627	0.020655427	0.009398016
Sep	0.701904865	0.258532689	0.0094184	0.017980298	0.012163748

Sheet 6

Periods	Hralthy & Fit S1	Average S2	Heavy S3	Overweight S4	Obese S5
Oct	0.258266819	0.381413911	0.234891676	0.078677309	0.046750285
Nov	0.397582277	0.413084339	0.125908313	0.050908415	0.012516656
Dec	0.15977287	0.196202429	0.304769143	0.225683296	0.113572262
Jan	0.013521808	0.028509129	0.04553549	0.306278654	0.606154919
Feb	0.003757541	0.008394183	0.0204992	0.272977086	0.69437199
Mar	0.004094108	0.00938026	0.02056624	0.319869454	0.646089938
Apr	0.328481772	0.263277685	0.119428581	0.184630916	0.104181046
May	0.16617002	0.183310051	0.309647947	0.199392902	0.14147908
Jun	0.458599204	0.31346642	0.104527431	0.0836706	0.039736345
Jul	0.755135822	0.236390804	0.003591969	0.003761403	0.001120003
Aug	0.744654557	0.251885666	0.001958792	0.000946845	0.00055414
Sep	0.733676382	0.249429066	0.005216484	0.00746809	0.004209978

Sheet 9

Periods	Hralthy & Fit S1	Average S2	Heavy S3	Overweight S4	Obese S5
Oct	0.112001187	0.220540968	0.407456856	0.191069574	0.068931415
Nov	0.086969526	0.140101779	0.33780924	0.239083161	0.196036294
Dec	0.06184236	0.102960781	0.274623122	0.318175275	0.242398462
Jan	0.017822369	0.023067057	0.085144554	0.359249153	0.514716866
Feb	0.079101144	0.096437035	0.128358538	0.309203689	0.386899594
Mar	0.262629855	0.200372917	0.112054289	0.278686839	0.1462561
Apr	0.14349504	0.160609052	0.295967915	0.231089572	0.16883842
May	0.118438536	0.14543814	0.301272404	0.258021002	0.176829918
Jun	0.043572837	0.081356577	0.087374747	0.279559437	0.508136402
Jul	0.368151132	0.30178884	0.129126558	0.119601358	0.081332112
Aug	0.409968234	0.366984616	0.024036148	0.088258259	0.110752743
Sep	0.426355693	0.364170403	0.022188491	0.069832098	0.117453315

Sheet 10

Periods	Hralthy & Fit S1	Average S2	Heavy S3	Overweight S4	Obese S5
Oct	0.377452818	0.418072741	0.128733908	0.060367454	0.015373078
Nov	0.436928867	0.409374905	0.107059518	0.038217467	0.008419244
Dec	0.333810902	0.397259566	0.199405571	0.046805279	0.022718681
Jan	0.216993809	0.188342621	0.163751228	0.200272738	0.230639604
Feb	0.035673646	0.031879224	0.092447732	0.339428382	0.500571016
Mar	0.024833869	0.037341721	0.141925882	0.453153002	0.342745526
Apr	0.073078865	0.095491706	0.257666575	0.325981683	0.247781171
May	0.40982655	0.295160762	0.115264926	0.119388709	0.060359052
Jun	0.093131187	0.15150862	0.119160759	0.227111632	0.409087801
Jul	0.670748431	0.28862922	0.01691656	0.016257144	0.007448645
Aug	0.786710328	0.210823899	0.001182972	0.000997425	0.000285375
Sep	0.748676303	0.248285506	0.001797565	0.000797569	0.000443058

Average

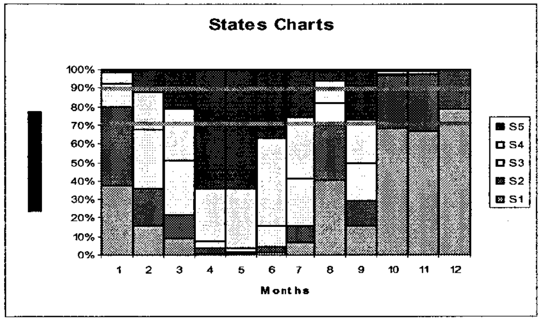
Periods	Hralthy & Fit S1	Average S2	Heavy S3	Overweight S4	Obese S5
1	0.231293366	0.302376485	0.254204573	0.146596996	0.065528581
2	0.20295483	0.265758618	0.245777576	0.161758811	0.123750166
3	0.150018986	0.224375239	0.285215415	0.187678309	0.152712052
4	0.074181834	0.084365106	0.150527059	0.314998297	0.375927704
5	0.049787223	0.05386246	0.076297702	0.311130548	0.508922067
6	0.06912311	0.065447718	0.07970137	0.349105076	0.436622726
7	0.124826396	0.12528494	0.180972247	0.274017957	0.294898462
8	0.161285719	0.162202948	0.156645243	0.211992857	0.307873234
9	0.199156788	0.175548599	0.123355561	0.211531755	0.290407297
10	0.592918991	0.282776199	0.039347684	0.046815981	0.038141145
11	0.686832892	0.266166768	0.007741541	0.017573497	0.021685302
12	0.710866819	0.260740372	0.004782477	0.009752834	0.013857498

Figure B7: The tables of the state transitions for the Experiment IV: Extensive-Policy

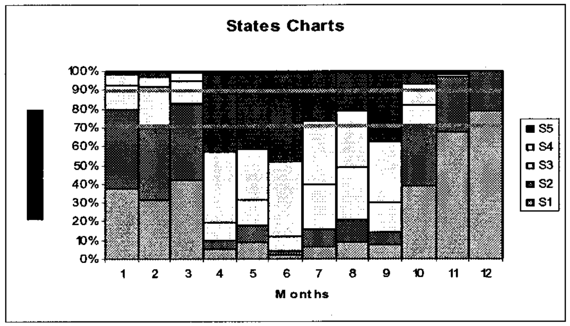
B.4.1 Graphs of the Experiment IV: Extensive-Policy Intervention

The graphs of the ten state transitions trials and their average for the Extensive-policy intervention are illustrated in the figure 67:

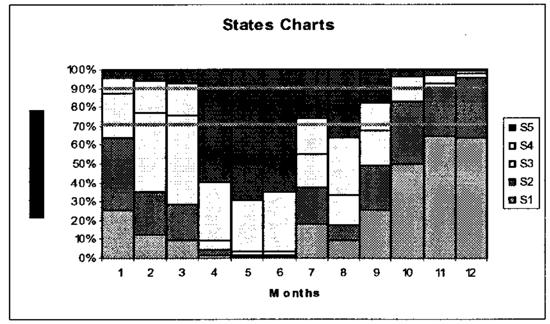
Trial # 1:



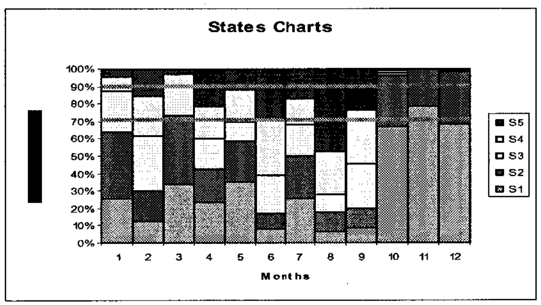
Trial # 2:



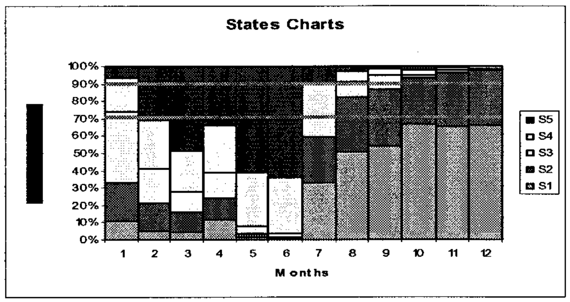
Trial # 3:



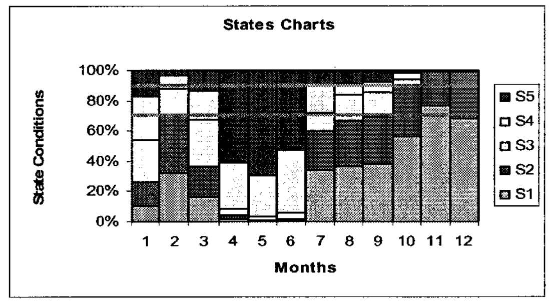
Trial # 4:



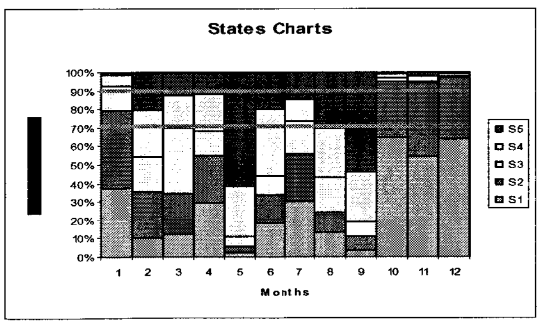
Trial # 5:



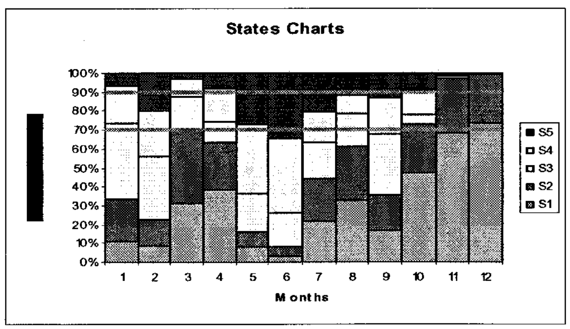
Trial # 6:



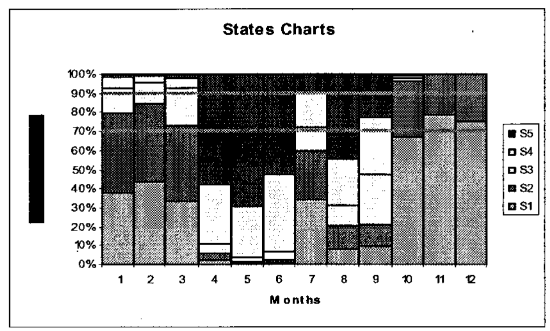
Trial # 7:



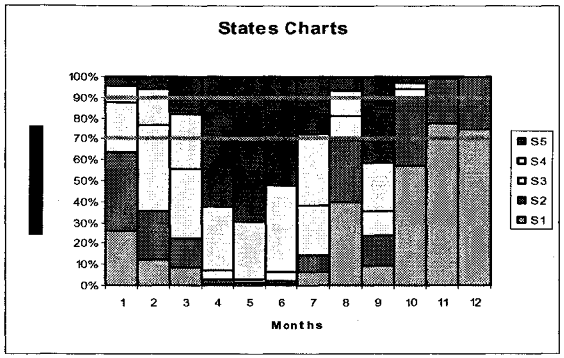
Trial # 8:



Trial # 9:



Trial # 10:



Extensive-Policy Intervention

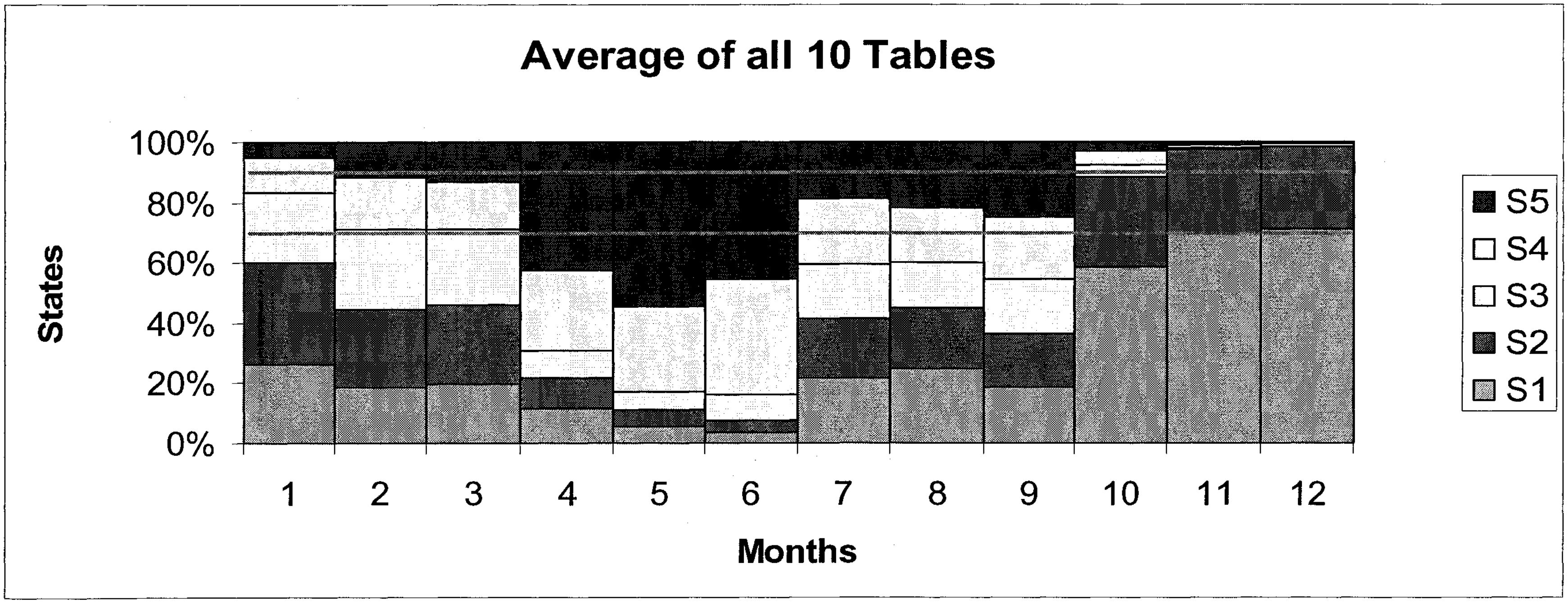
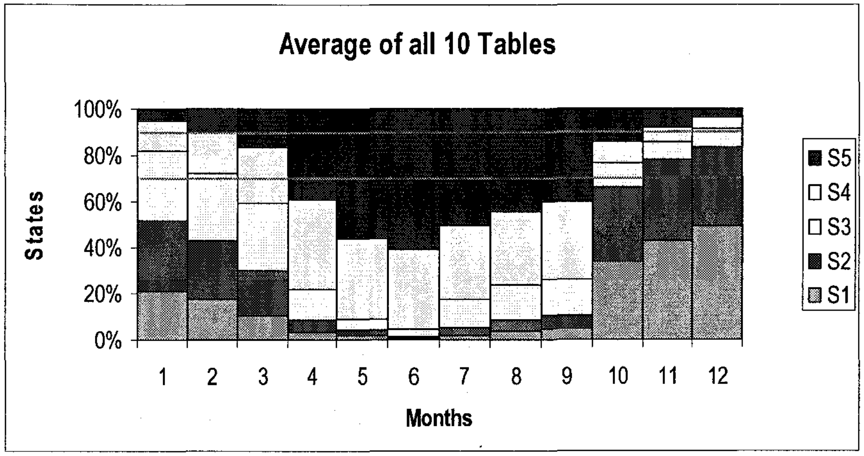


Figure B8: The graphs of the state transitions for the Experiment IV: Extensive-Policy

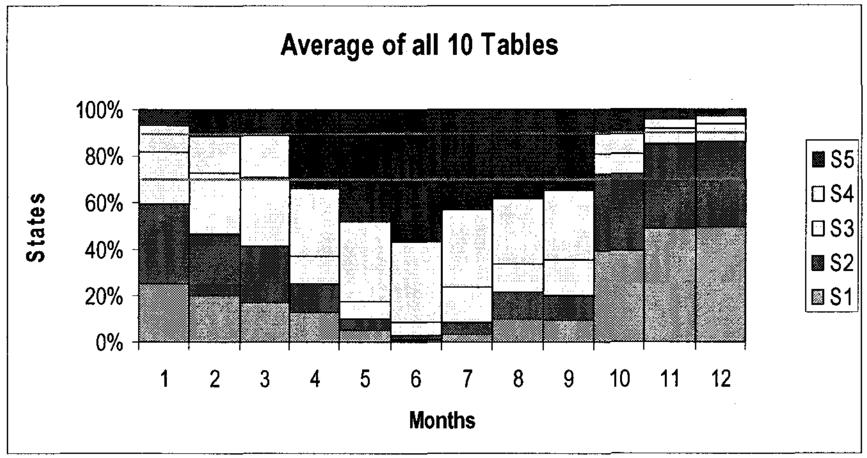
B.5 Final Graphs Comparison

The following graphs are based on the average of all ten trials for each Experiment:

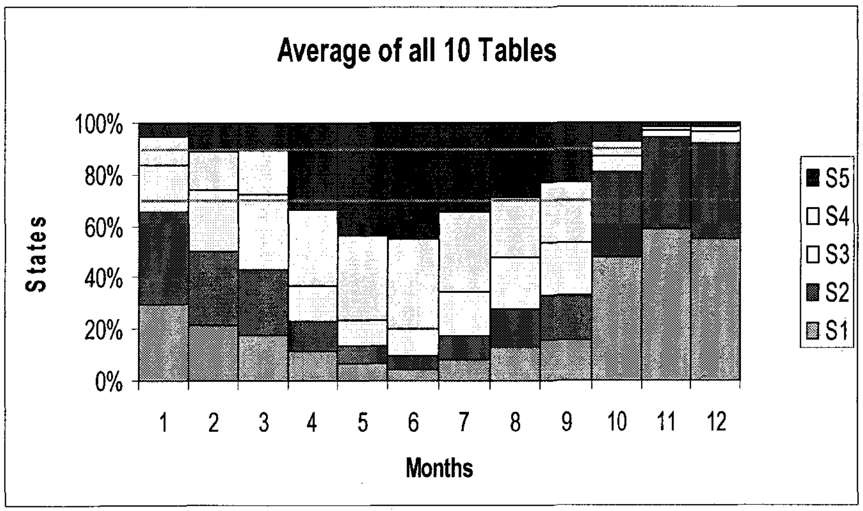
No-Policy Intervention



Low-Policy Intervention



Moderate-Policy Intervention



Extensive-Policy Intervention

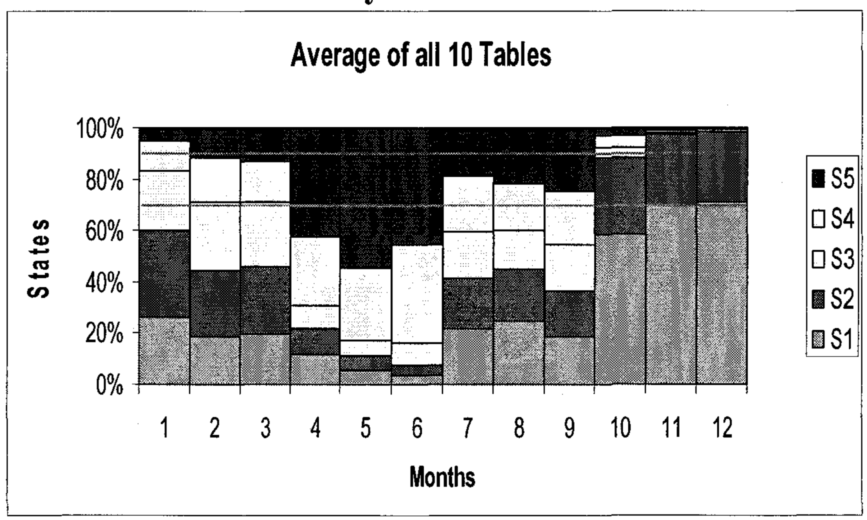


Figure B9: The final demonstration of the average of all four experiment graphs

APPENDIX C:
Cost Analysis

Appendix C demonstrates the cost analysis of all four experiment models: I. No-Policy intervention, II. Low-Policy intervention, Intermediate-Policy intervention and Extensive-Policy intervention scenarios in a case study for the obesity example. Decision trees are used to choose the most cost effective decision. The results are based on a simulation model and the outcome for each simulation may differ from other simulations.

All results come from the ten (10) trials for a period of 12 months (one year for each). Their correspondent's total costs for each experiment are illustrated for comparison. The total costs have come from the total alarms' costs plus total hearth costs.

C.1 Experiment I: No Policy Intervention Costs

The following presents the costs related to each trial in No-Policy intervention model, as well as total costs in all trials.

	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Sub-total
Trial # 1	$1,433.34	$880.10	$1,272.33	$1,560.08	$2,083.07	$2,174.20	$1,678.52	$935.58	$1,322.92	$681.43	$287.08	$384.59	$14,693.25
Trial # 2	$1,411.20	$1,543.64	$1,591.17	$1,267.33	$2,037.70	$2,355.28	$2,294.19	$1,689.37	$1,377.22	$322.24	$396.66	$425.31	$16,711.33
Trial # 3	$1,411.20	$1,543.64	$960.08	$1,595.23	$1,266.11	$1,690.21	$936.20	$621.45	$849.75	$291.68	$459.11	$439.98	$12,064.64
Trial # 4	$449.29	$508.03	$769.16	$1,555.13	$2,300.45	$2,380.80	$1,639.30	$1,941.08	$2,007.10	$1,545.79	$1,371.83	$996.43	$17,464.39
Trial # 5	$603.70	$568.34	$556.06	$781.75	$810.45	$811.22	$1,276.71	$1,433.69	$2,179.51	$1,601.45	$452.54	$436.89	$11,512.29
Trial # 6	$603.70	$568.34	$1,298.76	$2,040.05	$2,167.91	$2,187.08	$1,681.55	$2,224.14	$2,277.85	$873.62	$1,016.05	$382.29	$17,321.33
Trial # 7	$1,411.20	$624.65	$427.66	$1,843.14	$1,837.91	$2,335.32	$2,292.70	$2,286.41	$2,055.55	$523.73	$458.98	$563.66	$16,660.89
Trial # 8	$449.29	$962.64	$1,328.23	$1,135.52	$2,010.10	$1,427.61	$1,228.45	$1,087.01	$1,026.68	$597.12	$643.17	$280.61	$12,176.42
Trial # 9	$603.70	$568.34	$556.06	$1,878.99	$2,337.25	$2,384.36	$2,296.45	$2,057.24	$2,029.46	$520.18	$274.09	$379.53	$15,885.64
Trial # 10	$1,411.20	$1,141.73	$1,706.70	$2,316.74	$2,382.32	$2,212.64	$1,686.49	$1,971.43	$2,012.97	$1,225.64	$940.78	$574.34	$19,582.97
Total	$9,787.79	$8,909.45	$10,466.21	$15,973.97	$19,233.26	$19,958.72	$17,010.57	$16,247.40	$17,138.99	$8,182.88	$6,300.30	$4,863.61	$154,073.15

Figure C1: The cost demonstration of ten trials in Experiment I

C.1.1: Total Alarms Costs for No-Policy Interventions

	Total Alarm 1	Total Alarm 2	Total Alarm 3
Trial # 1	0	0	0
Trial # 2	0	0	0
Trial # 3	0	0	0
Trial # 4	0	0	0
Trial # 5	0	0	0
Trial # 6	0	0	0
Trial # 7	0	0	0
Trial # 8	0	0	0
Trial # 9	0	0	0
Trial # 10	0	0	0
SUM:	0	0	0
Average:	0	0	0
Total Alarms' cost:			$0

Figure C2: The cost demonstration of the alarms for the experiment I: No-Policy intervention

C.1.2: Final Costs for No-Policy Interventions

	Total cost
sheet # 1	$16,022.30
sheet # 2	$16,711.01
sheet # 3	$16,411.61
sheet # 4	$17,905.12
sheet # 5	$14,720.83
sheet # 6	$14,478.82
sheet # 7	$14,107.86
sheet # 8	$17,020.73
sheet # 9	$12,361.48
sheet # 10	$15,002.81
Total:	$154,742.57

Total Alarms' cost:		Total Health Cares' Cost:		Sum Total:
$0	+	$154,742.57	:	$154,742.57

Figure C3: The total cost demonstration of the Experiment I: No-Policy intervention

C.2 Experiment II: Low-Policy Intervention Costs

The following presents the costs related to each trial in Low-Policy intervention model, as well as total costs in all trials.

	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Sub-total
Trial # 1	$603.70	$813.49	$927.09	$2,210.99	$2,179.68	$1,874.64	$1,201.76	$2,119.90	$2,166.98	$1,259.13	$309.15	$391.62	$16,058.13
Trial # 2	$449.29	$740.63	$894.64	$1,595.18	$2,089.22	$2,163.46	$959.20	$2,081.73	$1,486.04	$1,047.34	$351.60	$632.32	$14,490.64
Trial # 3	$449.29	$508.03	$533.01	$1,190.06	$2,227.95	$2,181.38	$1,932.82	$1,269.88	$1,857.19	$457.85	$269.27	$292.62	$13,169.35
Trial # 4	$449.29	$508.03	$1,241.47	$994.78	$2,200.02	$1,877.16	$2,152.63	$1,513.84	$1,515.01	$412.29	$312.15	$393.33	$13,570.00
Trial # 5	$1,166.22	$1,663.79	$846.54	$1,940.90	$2,341.23	$2,384.24	$1,958.01	$1,283.11	$1,419.52	$312.88	$473.63	$270.98	$16,061.04
Trial # 6	$449.29	$962.64	$483.58	$2,123.61	$1,813.92	$1,765.54	$1,434.80	$2,182.97	$2,178.19	$338.88	$301.01	$297.34	$14,331.76
Trial # 7	$603.70	$427.45	$729.34	$901.99	$2,181.95	$1,379.56	$1,195.10	$2,065.28	$1,893.92	$464.52	$269.68	$259.28	$12,371.77
Trial # 8	$859.03	$516.67	$536.05	$771.19	$1,537.96	$2,291.44	$1,944.30	$2,156.11	$1,333.42	$321.06	$262.75	$375.30	$12,905.28
Trial # 9	$449.29	$962.64	$664.23	$1,905.17	$1,807.96	$2,326.28	$1,407.73	$1,457.96	$762.03	$534.39	$277.78	$449.87	$13,005.31
Trial # 10	$603.70	$1,330.34	$1,056.92	$1,422.65	$2,273.23	$2,187.44	$2,188.42	$943.66	$1,330.37	$307.90	$392.16	$661.72	$14,698.52
													$140,661.78
Total	$6,082.76	$8,433.70	$7,912.87	$15,056.53	$20,653.10	$20,431.14	$16,374.77	$17,074.45	$15,942.67	$5,456.24	$3,219.18	$4,024.37	$140,661.78

Figure C4: The cost demonstration of ten trials in Experiment II

C.2.1: Total Alarms Costs for Low-Policy Interventions

Canada's population was estimated to be 33,098,932 in July 2006.

* "Health care spending in Canada for 2006 was forecast to be $148 billion or $4,548 per person (CIHI, 2006)." http://www.fraserinstitute.ca

- Assume that obesity health cost is approximately $2,000 out of $4,548.
- Therefore Average Total monthly obesity health costs (Canada) are $5,516 billion.

HCC: Health Care Cost / Population / Month

	HCC/Pop/m	Assumed Portions /Scale	Round value per Million
Fit & healthy	$5,516,488,667	0.25	$1,379
Average	$5,516,488,667	0.55	$3,034
Above Average	$5,516,488,667	1	$5,516
Overweight	$5,516,488,667	2	$11,033
Obese	$5,516,488,667	4	$22,066

S1	S2	S3	S4	S5
$1,379	$3,034	$5,516	$11,033	$22,066

Figure C5: The cost demonstration of the health status

Alarm 1: Bar code alarm for more than 10% and less than 30% changes

S1-Cost	S2-Cost	S3-Cost	S4-Cost	S5-Cost
$1,379	$3,034	$5,516	$11,033	$22,066

	Total Alarm 1	Total Alarm 2	Total Alarm 3
Trial # 1	2	3	0
Trial # 2	0	5	0
Trial # 3	2	4	0
Trial # 4	4	2	0
Trial # 5	2	3	0
Trial # 6	1	6	0
Trial # 7	1	6	0
Trial # 8	1	5	0
Trial # 9	1	3	0
Trial # 10	2	4	0
SUM:	16	41	0
Average:	2	4	0
	$1,379	$2,758	$5,517
	Total Alarm 1	Total Alarm 2	Total Alarm 3
Sub-Total	$22,064	$113,088	$0 : ====>

Total Alarm costs:	
Trial # 1	$11,032.75
Trial # 2	$13,791.25
Trial # 3	$13,791.00
Trial # 4	$11,032.50
Trial # 5	$11,032.75
Trial # 6	$17,928.50
Trial # 7	$17,928.50
Trial # 8	$15,170.25
Trial # 9	$9,653.75
Trial # 10	$13,791.00
Total:	$135,152.25
Total Alarms' cost:	$135,152.25

Figure C6: The cost demonstration of the alarms for the experiment II: Low-Policy intervention

C.2.2: Final Costs for Low-Policy Interventions

Total Alarm costs:			Health cost		Total Cost
Trial # 1	$11,032.75	+	$13,540.43	:=	$24,573.18
Trial # 2	$13,791.25	+	$15,437.57	:=	$29,228.82
Trial # 3	$13,791.00	+	$14,450.77	:=	$28,241.77
Trial # 4	$11,032.50	+	$12,241.74	:=	$23,274.24
Trial # 5	$11,032.75	+	$13,786.03	:=	$24,818.78
Trial # 6	$17,928.50	+	$16,184.13	:=	$34,112.63
Trial # 7	$17,928.50	+	$17,419.43	:=	$35,347.93
Trial # 8	$15,170.25	+	$13,481.17	:=	$28,651.42
Trial # 9	$9,653.75	+	$12,254.26	:=	$21,908.01
Trial # 10	$13,791.00	+	$16,244.30	:=	$30,035.30
Total:	$135,152.25	+	$145,039.83	:=	$280,192.08

Figure C7: The total cost demonstration of the Experiment II: Low-Policy intervention

C.3 Experiment III: Moderate-policy intervention costs

The following presents the costs related to each trial in Moderate-Policy intervention model, as well as total costs in all trials.

	1	2	3	4	5	6	7	8	9	10	11	12	
	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Sub-total
Trial # 1	$859.03	$946.91	$744.10	$1,535.66	$1,710.06	$2,313.83	$1,553.39	$2,098.51	$2,167.39	$492.04	$756.48	$314.83	$15,492.21
Trial # 2	$1,411.20	$751.95	$445.59	$722.01	$1,914.06	$1,809.95	$1,450.04	$1,787.27	$1,193.88	$600.22	$645.15	$495.78	$13,227.11
Trial # 3	$859.03	$1,272.37	$1,753.06	$2,099.14	$1,828.06	$2,326.16	$1,402.93	$656.12	$871.11	$331.97	$263.74	$258.89	$13,922.57
Trial # 4	$1,166.22	$751.43	$1,193.75	$2,235.39	$1,874.40	$1,784.35	$1,864.21	$1,450.50	$723.29	$524.92	$277.32	$293.90	$14,139.68
Trial # 5	$1,411.20	$506.68	$1,019.98	$2,204.42	$1,879.11	$2,131.33	$946.66	$1,331.54	$1,008.61	$844.66	$276.56	$380.38	$13,941.14
Trial # 6	$859.03	$946.91	$1,019.98	$1,044.50	$2,209.16	$1,399.34	$1,745.56	$2,116.16	$905.04	$807.85	$466.06	$273.23	$13,792.81
Trial # 7	$859.03	$699.53	$859.13	$1,400.86	$1,446.30	$960.01	$1,782.69	$781.56	$1,731.16	$441.59	$313.11	$298.90	$11,573.86
Trial # 8	$449.29	$962.64	$917.94	$1,971.90	$2,345.14	$2,384.66	$1,958.09	$1,283.16	$1,998.32	$783.50	$288.19	$260.57	$15,603.38
Trial # 9	$859.03	$1,272.37	$727.39	$1,915.64	$1,810.50	$2,326.59	$999.14	$2,092.29	$1,283.31	$293.73	$585.17	$631.67	$14,796.84
Trial # 10	$603.70	$427.45	$385.25	$1,830.57	$1,785.51	$1,711.15	$1,819.11	$1,435.77	$1,078.60	$571.27	$478.06	$322.59	$12,449.02
													$138,938.61
total	$9,336.74	$8,538.22	$9,066.16	$16,960.09	$18,802.30	$19,147.36	$15,521.82	$15,032.87	$12,960.72	$5,691.75	$4,349.84	$3,530.73	$138,938.61

Figure C8: The cost demonstration of ten trials in Experiment III

C.3.1: Total Alarms Costs for Moderate-Policy Interventions

	Total Alarm 1	Total Alarm 2	Total Alarm 3
Trial # 1	0	5	0
Trial # 2	2	5	0
Trial # 3	1	6	0
Trial # 4	0	7	0
Trial # 5	0	6	0
Trial # 6	0	5	0
Trial # 7	2	4	0
Trial # 8	1	7	0
Trial # 9	1	6	0
Trial # 10	0	6	0
SUM:	7	57	0
Average:	1	6	0
	$1,379	$2,758	$5,517
	Total Alarm 1	Total Alarm 2	Total Alarm 3
Sub-Total	$9,653	$157,220	$0

: ====>

Total Alarm costs:	
Trial # 1	$13,791.25
Trial # 2	$16,549.25
Trial # 3	$17,928.50
Trial # 4	$19,307.75
Trial # 5	$16,549.50
Trial # 6	$13,791.25
Trial # 7	$13,791.00
Trial # 8	$20,686.75
Trial # 9	$17,928.50
Trial # 10	$16,549.50
Total:	$166,873.25

Total Alarms' cost: $166,873.25

Figure C9: The cost demonstration of the alarms for the experiment III: Moderate-Policy

C.3.2: Final Costs for Moderate-Policy Interventions

Total Alarm costs:			Health cost		Total Cost
Trial # 1	$13,791.25	+	$13,467.63	:=	$27,258.88
Trial # 2	$16,549.25	+	$13,431.82	:=	$29,981.07
Trial # 3	$17,928.50	+	$16,051.41	:=	$33,979.91
Trial # 4	$19,307.75	+	$14,963.70	:=	$34,271.45
Trial # 5	$16,549.50	+	$12,315.90	:=	$28,865.40
Trial # 6	$13,791.25	+	$12,728.45	:=	$26,519.70
Trial # 7	$13,791.00	+	$12,945.18	:=	$26,736.18
Trial # 8	$20,686.75	+	$15,744.42	:=	$36,431.17
Trial # 9	$17,928.50	+	$14,707.72	:=	$32,636.22
Trial # 10	$16,549.50	+	$14,047.05	:=	$30,596.55
Total:	$166,873.25	+	$140,403.27	:=	$307,276.52

Figure C10: The final cost demonstration of the experiment III: Moderate-Policy

C.4 Experiment IV: Extensive-Policy Intervention Costs

The following presents the costs related to each trial in Extensive-Policy intervention model, as well as total costs in all trials.

	1	2	3	4	5	6	7	8	9	10	11	12	
	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Sub-total
Trial # 1	$449.29	$962.64	$917.94	$1,356.06	$1,631.22	$2,010.85	$753.56	$1,731.40	$981.64	$465.00	$321.87	$299.15	$11,880.60
Trial # 2	$859.03	$651.41	$546.93	$1,827.23	$2,118.30	$1,771.61	$1,121.57	$497.17	$1,225.71	$527.15	$264.06	$222.96	$11,633.14
Trial # 3	$449.29	$508.03	$1,023.87	$1,962.47	$1,824.13	$1,717.69	$1,824.48	$1,379.57	$2,006.02	$304.84	$241.10	$304.04	$13,545.53
Trial # 4	$603.70	$427.45	$385.25	$1,830.57	$2,118.86	$2,079.03	$1,193.76	$1,589.59	$2,038.18	$694.06	$281.47	$277.64	$13,519.56
Trial # 5	$603.70	$427.45	$1,162.32	$1,985.66	$2,346.42	$2,297.61	$2,171.64	$1,876.84	$1,393.44	$356.85	$407.73	$250.24	$15,279.88
Trial # 6	$603.70	$813.49	$1,180.18	$1,013.69	$1,957.11	$2,140.78	$776.69	$658.00	$1,327.85	$549.42	$266.41	$223.09	$11,510.40
Trial # 7	$603.70	$427.45	$729.34	$1,542.41	$1,136.71	$2,233.68	$1,886.60	$1,096.66	$490.82	$332.24	$243.98	$257.29	$10,980.85
Trial # 8	$859.03	$483.18	$696.04	$2,137.95	$1,861.35	$2,266.79	$1,215.87	$514.97	$861.70	$258.33	$222.58	$252.93	$11,630.72
Trial # 9	$859.03	$1,201.55	$548.69	$1,120.22	$1,554.87	$1,994.14	$1,867.08	$2,106.02	$731.79	$396.40	$250.63	$259.12	$12,889.55
Trial # 10	$603.70	$568.34	$420.19	$2,109.51	$1,853.07	$1,723.91	$2,105.84	$1,432.50	$2,020.93	$416.86	$230.75	$220.70	$13,706.27
													$126,576.52
Total	$6,494.14	$6,470.98	$7,610.74	$16,885.77	$18,402.05	$20,236.09	$14,917.08	$12,882.71	$13,078.08	$4,301.15	$2,730.56	$2,567.17	$126,576.52

Figure C11: The cost demonstration of ten trials in experiment IV

C.4.1: Total Alarms Costs for Extensive-Policy Interventions

	Total Alarm 1	Total Alarm 2	Total Alarm 3
Trial # 1	3	1	8
Trial # 2	1	1	9
Trial # 3	1	1	7
Trial # 4	0	1	8
Trial # 5	0	2	9
Trial # 6	3	1	8
Trial # 7	1	1	10
Trial # 8	3	1	8
Trial # 9	3	1	8
Trial # 10	2	1	8
SUM:	17	11	83
Average:	2	1	8
	$1,379	$2,758	$5,517
	Total Alarm 1	Total Alarm 2	Total Alarm 3
Sub-Total	$23,443	$30,341	$457,870

: ====>

Total Alarm costs:	
Trial # 1	$51,027.25
Trial # 2	$53,785.75
Trial # 3	$42,752.75
Trial # 4	$46,890.25
Trial # 5	$55,165.00
Trial # 6	$51,027.25
Trial # 7	$59,302.25
Trial # 8	$51,027.25
Trial # 9	$51,027.25
Trial # 10	$49,648.25
Total:	$511,653.25

Total Alarms' cost: $511,653.25

Figure C12: The cost demonstration of the alarms for the Experiment IV: Extensive-Policy

C.4.2: Final Costs for Extensive-Policy Interventions

Total Alarm costs:			Health cost		Total Cost
Trial # 1	$51,027.25	+	$15,923.91	:=	$66,951.16
Trial # 2	$53,785.75	+	$13,130.96	:=	$66,916.71
Trial # 3	$42,752.75	+	$11,997.62	:=	$54,750.37
Trial # 4	$46,890.25	+	$13,343.71	:=	$60,233.96
Trial # 5	$55,165.00	+	$12,437.69	:=	$67,602.69
Trial # 6	$51,027.25	+	$11,339.23	:=	$62,366.48
Trial # 7	$59,302.25	+	$15,249.36	:=	$74,551.61
Trial # 8	$51,027.25	+	$10,274.27	:=	$61,301.52
Trial # 9	$51,027.25	+	$12,841.25	:=	$63,868.50
Trial # 10	$49,648.25	+	$13,994.47	:=	$63,642.72
Total:	$511,653.25		$130,532.46		$642,185.71

Figure C13: The final cost demonstration of the Experiment IV: Extensive-Policy

APPENDIX D:
Cost Decision

Appendix D, demonstrates the total cost in ten trials of all four case models in an example obesity case study:

I. No-Policy intervention
II. Low-Policy intervention
III. Intermediate-Policy intervention
IV. Extensive-Policy intervention

Through the use of a decision-making tree, the final costs for each case will be compared and a final decision for the best model will be determined. This final decision will be based on best possible model's prevention outcome with its lowest possible cost. The results are based on a simulation model and the outcome for each simulation may differ from other simulations. Through many simulations, the result supports between No-Policy to Low Policy interventions.

All results came from the ten (10) trials for a period of 12 months (one year for each). Their correspondent's total costs for each experiment are illustrated for comparison. The total costs have come from the total alarms' costs plus total hearth costs. A decision-making tree has been used for this simulation to find the best possible experiment in each simulation.

D.1: Decision Trees for Ten Trials

The following figures illustrate the decision trees for each trail:

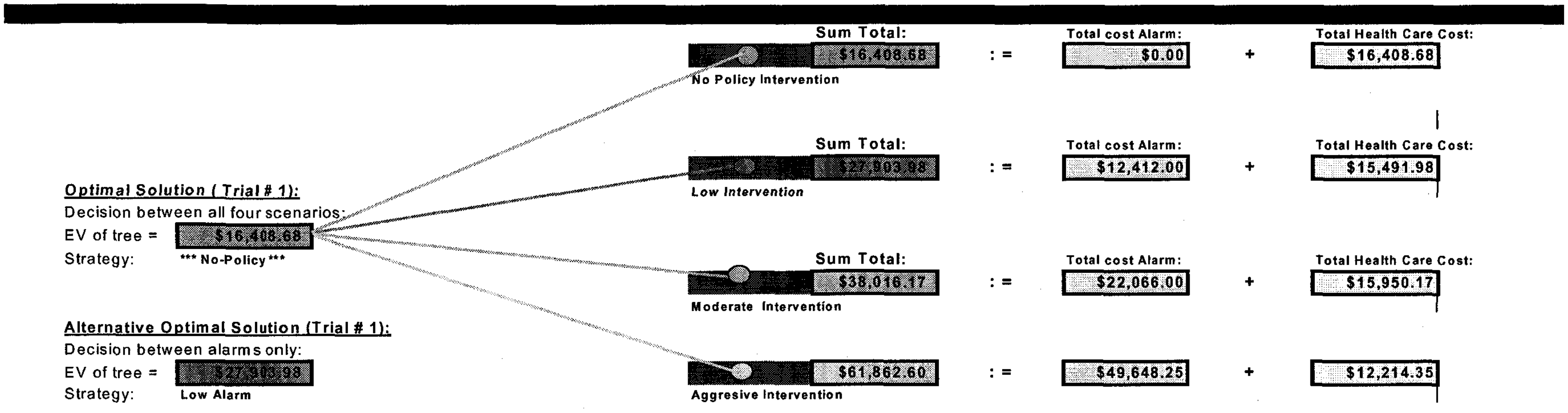


Figure D1: The decision tree for the trial # 1

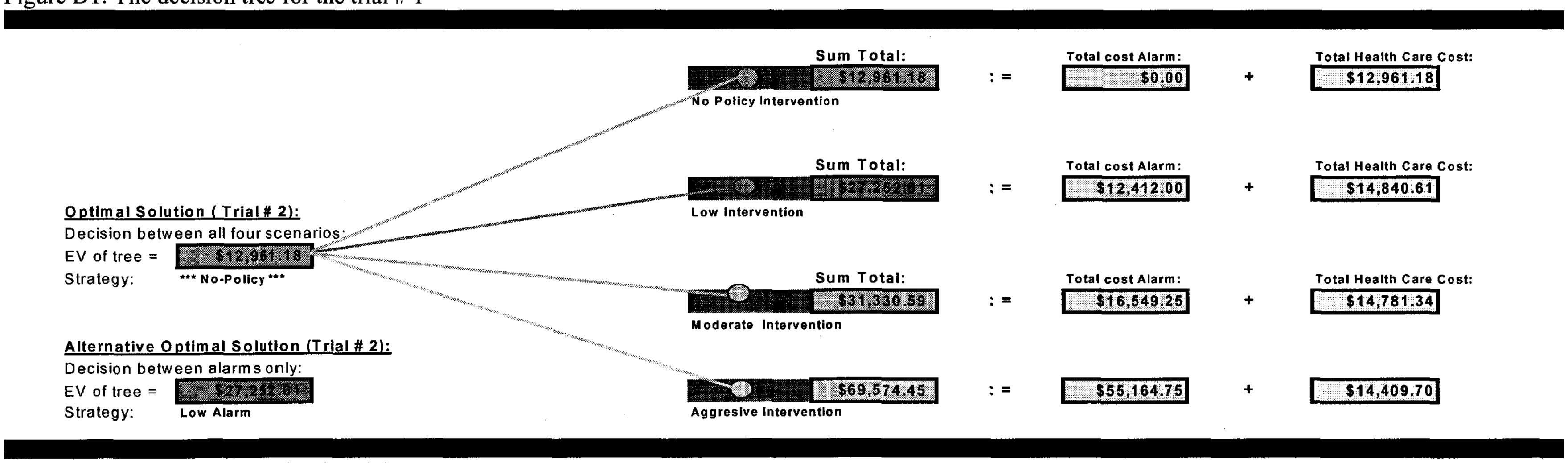


Figure D2: The decision tree for the trial # 2

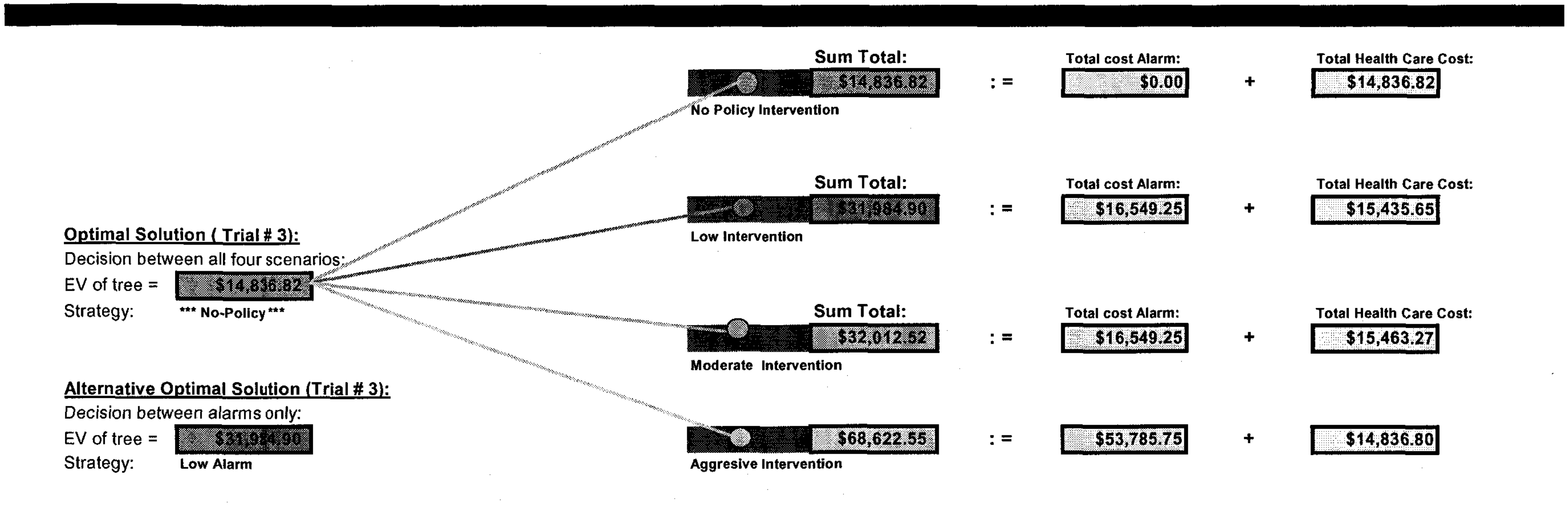


Figure D3: The decision tree for the trial # 3

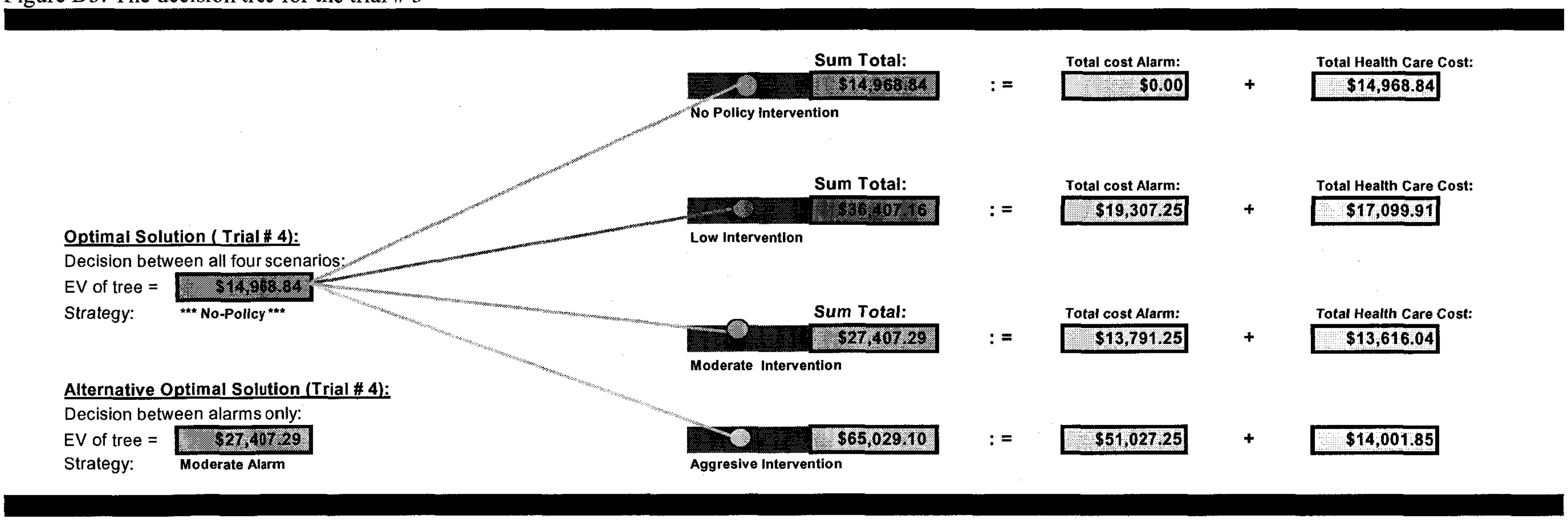


Figure D4: The decision tree for the trial # 4

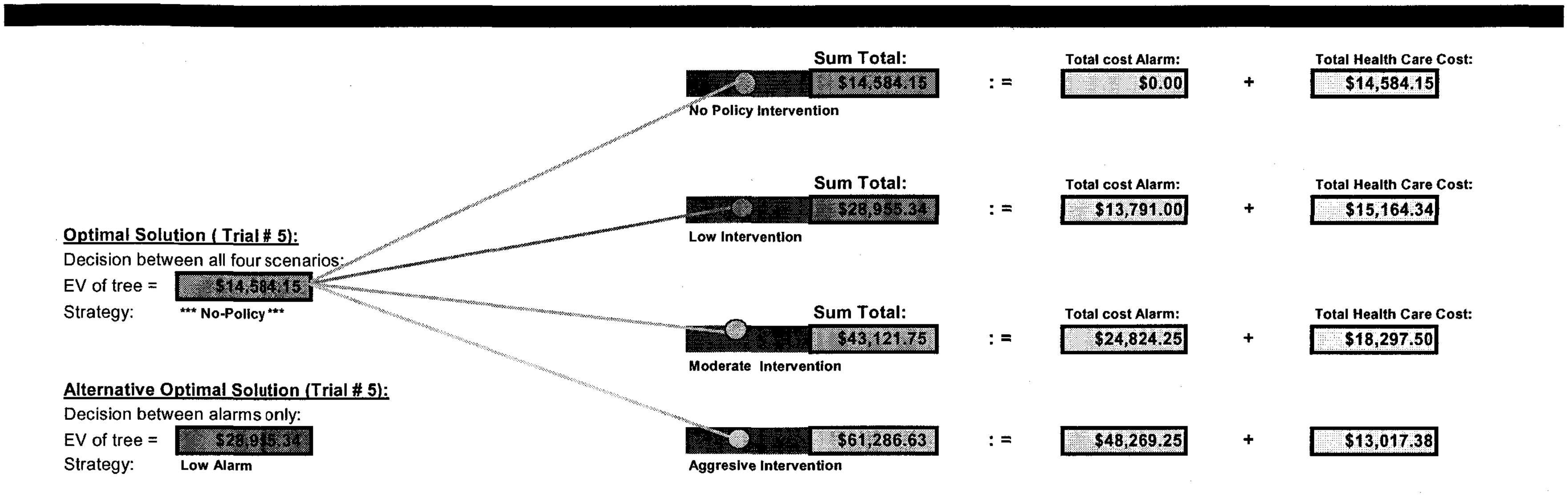


Figure D5: The decision tree for the trial # 5

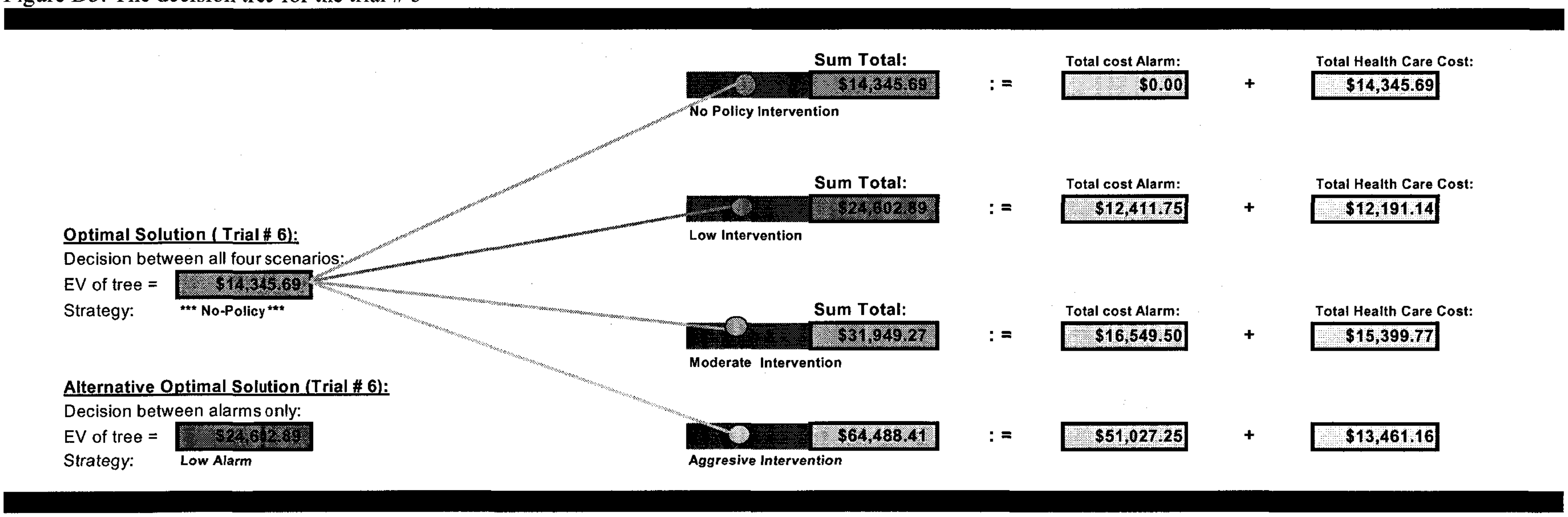


Figure D6: The decision tree for the trial # 6

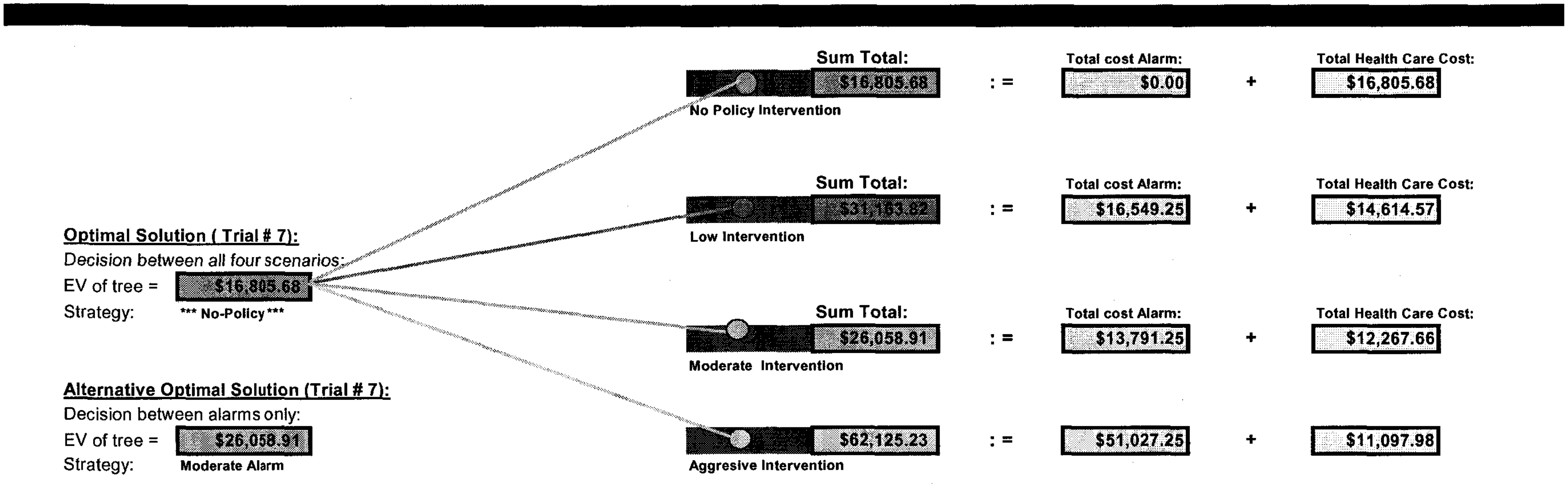


Figure D7: The decision tree for the trial # 7

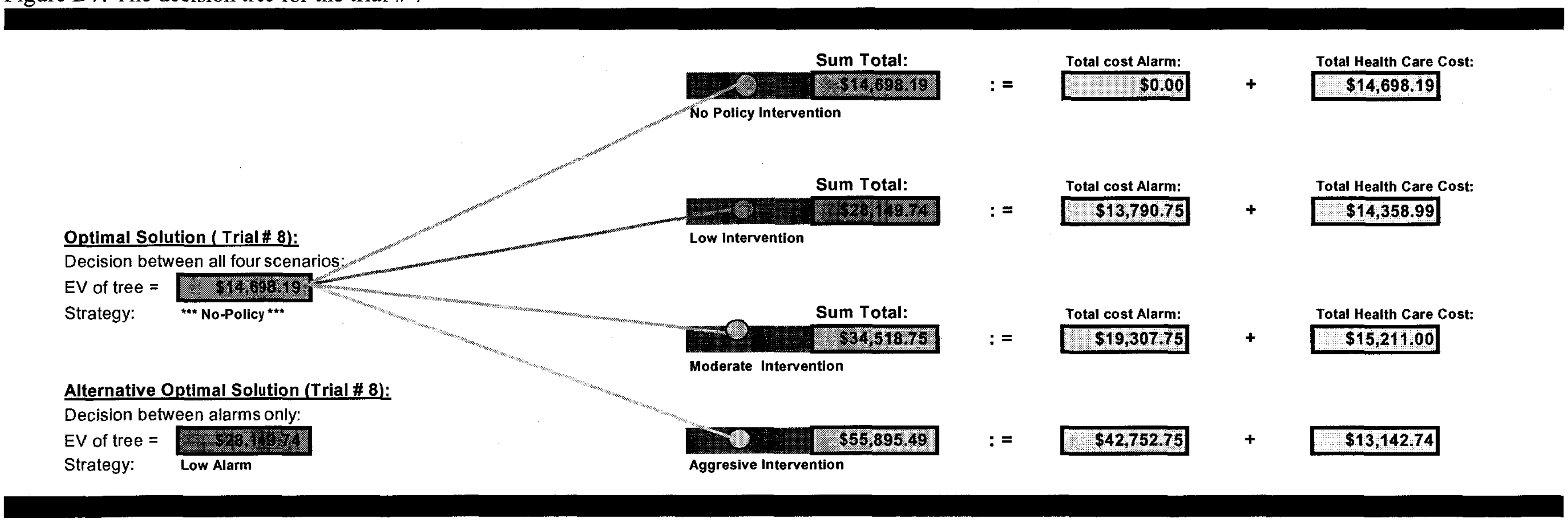


Figure D8: The decision tree for the trial # 8

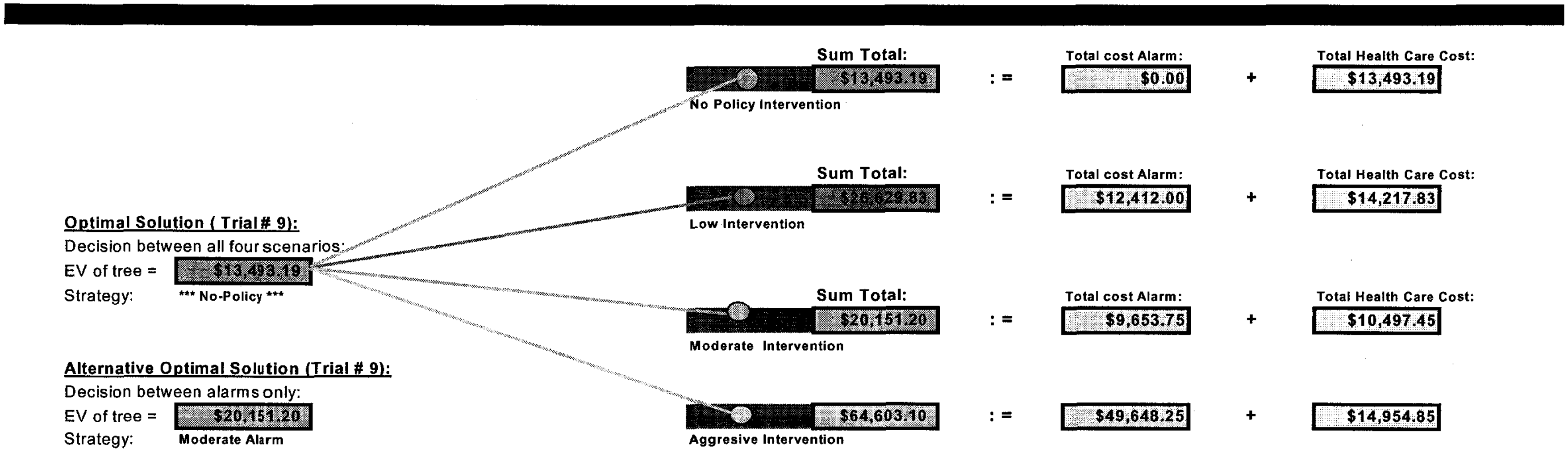


Figure D9: The decision tree for the trial # 9

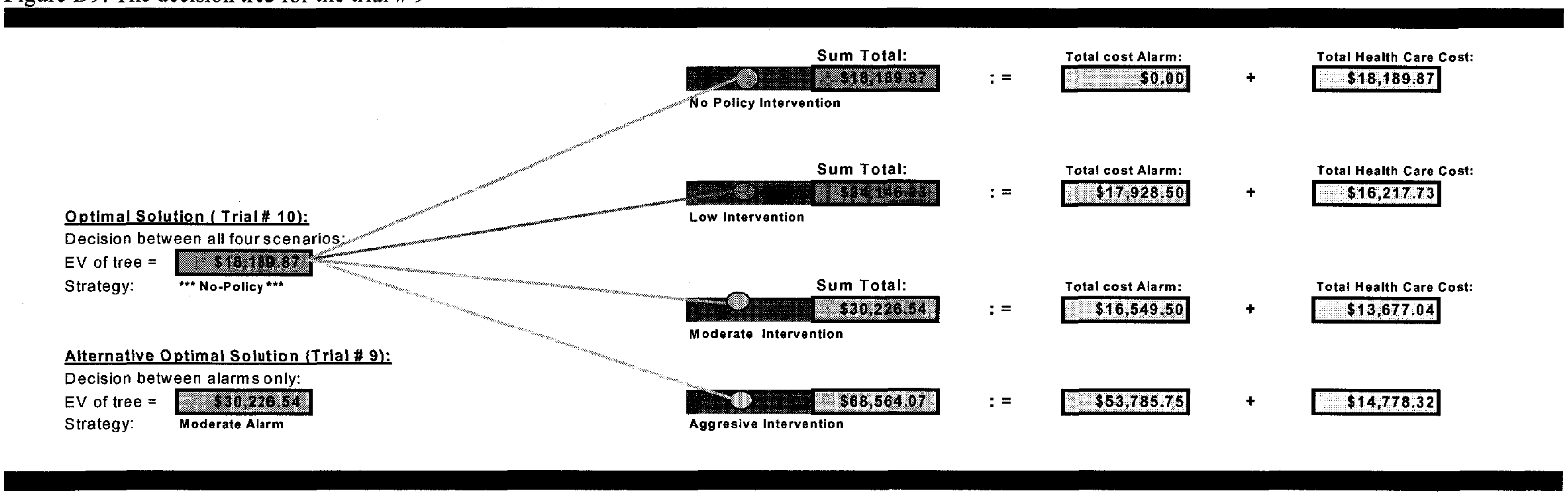


Figure D10: The decision tree for the trial # 10

D.2 Collected Data from the Decision Trees for all ten Trials

The following figure displays the costs of each trial for all different experiments:

Health Cost	Trial # 1	Trial # 2	Trial # 3	Trial # 4	Trial # 5	Trial # 6	Trial # 7	Trial # 8	Trial # 9	Trial # 10
No-Policy Intervention	$16,408.68	$12,961.18	$14,836.82	$14,968.84	$14,584.15	$14,345.69	$16,805.68	$14,698.19	$13,493.19	$18,189.87
Low Intervention	$27,903.98	$27,252.61	$31,984.90	$36,407.16	$28,955.34	$24,602.89	$31,163.82	$28,149.74	$26,629.83	$34,146.23
Moderate Intervention	$38,016.17	$31,330.59	$32,012.52	$27,407.29	$43,121.75	$31,949.27	$26,058.91	$34,518.75	$20,151.20	$30,226.54
Aggressive Intervention	$61,862.60	$69,574.45	$68,622.55	$65,029.10	$61,286.63	$64,488.41	$62,125.23	$55,895.49	$64,603.10	$68,564.07
Decision between all four scenarios:	$16,408.68	$12,961.18	$14,836.82	$14,968.84	$14,584.15	$14,345.69	$16,805.68	$14,698.19	$13,493.19	$18,189.87
Decision between alarms only:	$27,903.98	$27,252.61	$31,984.90	$27,407.29	$28,955.34	$24,602.89	$26,058.91	$28,149.74	$20,151.20	$30,226.54

Table D1: The table of the ten trials for all cases for comparison

D.3 Final Decision Tree Based on all ten Trials

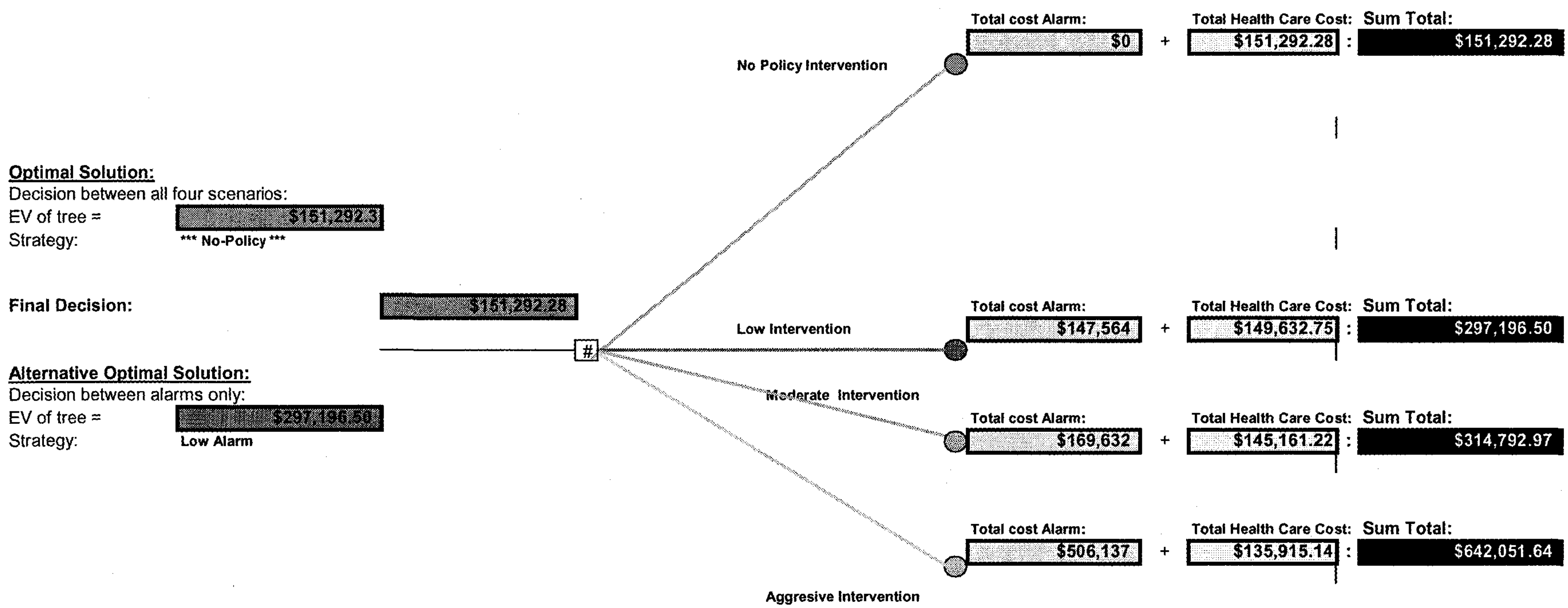


Figure D11: The decision tree for all experiment trials

D.4 Final Comparison Graphs of all Ten Trials

The following tables represent the alarm costs, health costs and the total cost of all models in all ten trials.

Alarm Cost	Trial # 1	Trial # 2	Trial # 3	Trial # 4	Trial # 5	Trial # 6	Trial # 7	Trial # 8	Trial # 9	Trial # 10	Total
No-Policy Intervention	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00	$0.00
Low Intervention	$12,412.00	$13,791.25	$20,686.50	$11,032.75	$12,411.75	$12,412.00	$13,791.25	$13,791.25	$15,170.00	$19,307.50	$144,806.25
Moderate Intervention	$13,791.25	$12,412.00	$20,686.75	$16,549.25	$16,549.25	$11,033.00	$16,549.50	$19,307.75	$17,928.50	$20,686.75	$165,494.00
Aggressive Intervention	$57,923.25	$51,027.25	$49,648.25	$46,890.25	$48,269.25	$51,027.25	$46,890.25	$48,269.25	$46,889.75	$51,027.25	$497,862.00

Health Cost	Trial # 1	Trial # 2	Trial # 3	Trial # 4	Trial # 5	Trial # 6	Trial # 7	Trial # 8	Trial # 9	Trial # 10	Total
No-Policy Intervention	$14,081.84	$13,191.85	$17,881.56	$13,199.69	$14,588.30	$16,938.07	$16,958.54	$17,327.31	$16,615.05	$14,868.01	$155,650.24
Low Intervention	$12,625.70	$14,283.57	$18,610.33	$13,128.84	$14,551.98	$14,932.89	$13,526.95	$15,257.06	$15,131.78	$17,706.88	$149,755.97
Moderate Intervention	$13,609.84	$12,968.30	$15,807.97	$14,000.58	$13,987.60	$11,442.36	$15,340.01	$16,486.50	$15,240.47	$17,373.09	$146,256.72
Aggressive Intervention	$13,801.84	$17,286.23	$13,277.26	$14,545.18	$14,113.38	$16,049.09	$10,605.83	$13,082.14	$8,971.75	$12,941.86	$134,674.57

Health Cost	Trial # 1	Trial # 2	Trial # 3	Trial # 4	Trial # 5	Trial # 6	Trial # 7	Trial # 8	Trial # 9	Trial # 10	Total
No-Policy Intervention	$14,081.84	$13,191.85	$17,881.56	$13,199.69	$14,588.30	$16,938.07	$16,958.54	$17,327.31	$16,615.05	$14,868.01	$155,650.24
Low Intervention	$25,037.70	$28,074.82	$39,296.83	$24,161.59	$26,963.73	$27,344.89	$27,318.20	$29,048.31	$30,301.78	$37,014.38	$294,562.22
Moderate Intervention	$27,401.09	$25,380.30	$36,494.72	$30,549.83	$30,536.85	$22,475.36	$31,889.51	$35,794.25	$33,168.97	$38,059.84	$311,750.72
Aggressive Intervention	$71,725.09	$68,313.48	$62,925.51	$61,435.43	$62,382.63	$67,076.34	$57,496.08	$61,351.39	$55,861.50	$63,969.11	$632,536.57
	$14,081.84	$13,191.85	$17,881.56	$13,199.69	$14,588.30	$16,938.07	$16,958.54	$17,327.31	$16,615.05	$14,868.01	

Table D2: The table of the ten trials for the cost demonstration all cases

The following graph shows the cost related charts of each trial for all four experiment models. Through comparison, it is obvious that the extensive model has a very high cost compare to the three other models. The lowest cost, in most cases, seems to be the no-policy intervention model. The results of the graph may vary in each simulation and no result is an absolute outcome.

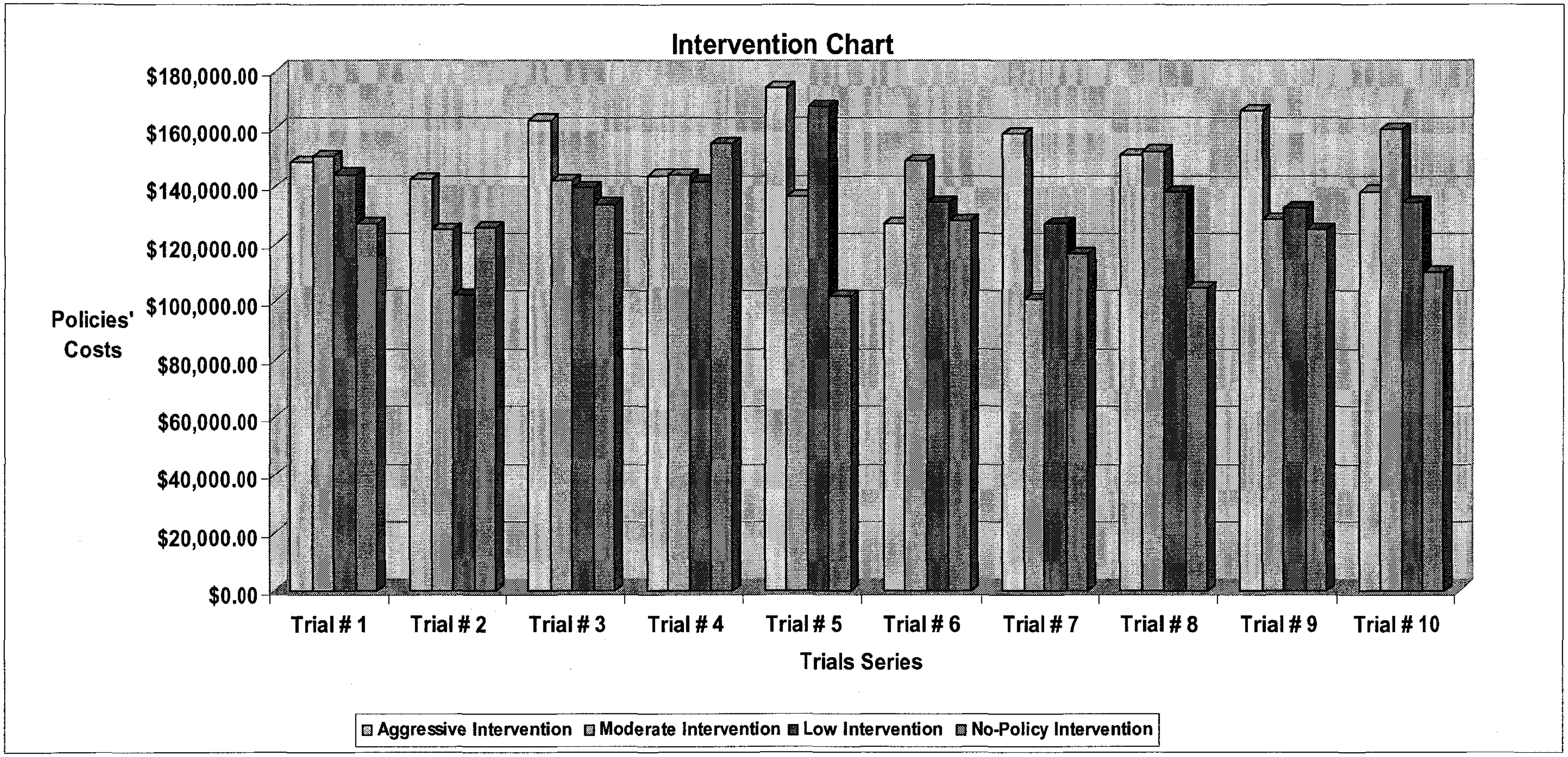


Figure D12: The graph of the cost related chart for the decision trees of the all cases