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Development of a Decision Support Framework for the Planning of Sustainable Transportation Systems

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DEVELOPMENT OF A DECISION SUPPORT FRAMEWORK FOR THE PLANNING OF SUSTAINABLE TRANSPORTATION SYSTEMS

by

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ABSTRACT

Development of a Decision Support Framework for the Planning of Sustainable Transportation Systems

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With the rapid increase in economic development throughout the world, there is stress on the resources used to support global economy, including petroleum, coal, silver, and water. Currently, the world is consuming energy at an unprecedented rate never seen before. The finite nature of such non-renewable natural resources as petroleum and coal puts pressure on the environmental system, and ultimately reduces the availability of resources for future generations. Hence, it is critical to develop planning and operational strategies that seek to achieve a sustainable use of existing natural resources.

With this motivation, this dissertation focuses to develop a decision support framework based on multiple performance measures for the planning of sustainable transportation systems. A holistic approach was adopted to compute performance indices for a System of Systems (SOS) including the Transportation, Activity, and Environmental systems. The performance indices were synthesized to calculate a composite sustainability index to evaluate the sustainability of the overall SOS. To help make better design and policy decisions at an aggregate level, a suitable modeling approach that captures the dynamic interactions within the SOS was formulated. A

method of system of ordinary differential equations was chosen to model the aggregated performance indices and their interdependencies over time. In addition, systems and control methodology was used in the development of optimal policies (with respect to investments in various systems) for decision making purposes.

The results indicated that the Transportation and Activity system both follow positive trend over the years whereas the Environmental system follows an overall negative trend. This is evident as continuous increase in growth and transportation will result in decreased performance of Environmental system over time. The results also highlighted periodic behavior with a phase lag for the performance of Transportation and the Activity system; the performance of Environment system decayed with time. In addition, the results demonstrated that it is possible to formulate an optimal control to predict investment decisions over time. Furthermore, the results from this research provided an alternate, cost-effective method to rank and prioritize projects based on sustainability index values.

The major contributions of this research are fourfold. The first contribution of this research is the development of a framework to generate sustainability indices for policy making considering, explicitly, multiple interdependent systems. This research is first of its kind to study the dynamical interactions between the three systems: Transportation, Activity, and Environment. The second contribution of this research is a detailed analysis to understand the dynamics of the three interdependent systems. Multiple insights were obtained from this research. The techniques learnt can be applied to perform multi-city network modeling through the concept of interconnected networks. In addition, the need to conserve the environment and preserve the resources is highlighted. The third contribution of this research work is development of control mechanisms to evaluate investment policies for the design of sustainable systems. Investment decisions were derived from the design. The fourth contribution of this research is the development of a framework to estimate sustainability indices for the evaluation and prioritization of transportation projects. Projects are prioritized and ranked based on the sustainability index values. The greater the sustainability index value, the higher is the project priority. This provides a comprehensive mechanism to incorporate information beyond traditional techniques.

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CHAPTER 1

INTRODUCTION

1.1 Background

The continuous appetite for natural resources by human race to support the growth and development has led to depletion of energy including petroleum, oil, coal, water etc. However, the limited availability of non-renewable resources such as petroleum and coal has resulted in environmental degradation, and hence endangers the availability of resources for future generations. As a result, it is important to develop planning and operational strategies that limits the misuse of natural resources and enable to utilize them in a sustainable manner.

Sustainability is a broad based theme and its significance has been widely recognized in multiple areas, such as transportation systems, global warming, climate change (Dawadi & Ahmad, 2012, 2013), hydrology (Forsee & Ahmad, 2011; Wu et al., 2013), and carbon footprint (Shrestha et al., 2011, 2012). As a result, decision makers have been enthusiastic to incorporate sustainable practices into various disciplines that help the environment, society and community livability. It is clear that a truly sustainable state for a system requires all the relevant interdependent sub-systems/sectors and components, at levels so that the consumption of and the impact on the natural and economic resources do not deplete or destroy those resources. Hence, the assessment of a system state requires a holistic analysis in order to consider all the relevant sectors and impacts (Mirchi et al., 2012). However, existing approaches used to study the sustainability of a transportation system are not comprehensive enough to include key interactions with other systems such as the environment, the economy, and society in general. For example, the current planning of transportation systems is limited in terms of the number, accuracy, length, and approaches used to consider simultaneously important characteristics, including energy consumption, emissions, accidents, congestion, reliability, economic growth, and such social impacts as human health. That is, the existing practices only consider some effects, the estimations are approximate (Paravantis & Georgakellos, 2007), and the analysis period is relatively short, in the order of 30 years (Huzayyin & Salem, 2012). In addition, these effects are synthetized only on the basis of approximated monetary considerations that are unlikely to capture the full extent of the effects, for instance, the financial cost of emissions or greenhouse gases (Litman, 2012; Zolnik, 2012). For example, Zheng et al. (2011) described various system indicators by primarily considering economic aspects. Although the study provided valuable insights about the quantification of the economic domain of transportation sustainability, it is primarily focused on the transportation sector.

The need for a sustainable transportation system has been widely regarded as one of the most important aspects for decision-making (Litman, 2007; Jeon et al., 2010). However, the interdependencies of the transportation system with other systems such as Activity, Environmental and Society make sustainability difficult to be considered explicitly. Several indicators involving the transportation system (TS), activity system (AS), and environmental system (ES) have been developed by a variety of researchers (Bell & Morse, 1999; Bossel, 2001; Paz et al., 2013). These indicators provided a tool to understand such systems. However, none of the systems can thrive on their own and in turn need the other for their growth and development. In the context of sustainability, it is difficult to isolate systems or narrow the analysis to a particular region. Different systems such as Transportation have interdependencies with other systems including the economy and the environment. For example, energy resources, which are part of the environmental system, are required by both the transportation sector and the economy. Hence, any policy or strategy affecting the consumption or production of energy has effects at least on the transportation, the economy, and the environment.

Many studies have focused on understanding the design and analysis of sustainable transportation systems (Cascetta, 2008; Manheim, 1979). Issues that have been discussed include the formulations, analysis, design, and computation of solutions to such problems through the use of appropriate policies, ranging from tolls and tradable pollution permits (Nagurney, 2000). Li et al. (2013) addressed the design of sustainable cordon toll pricing schemes and the findings suggest that the interdependencies among cordon toll scheme, traffic congestion, environmental effects, and urban population distribution. The study also revealed the effects of subsidizing the retrofit of old vehicles on reduction in emissions and determined the optimal subsidy policy for social welfare. Szeto et al. (2013) discussed a sustainable road network design and provided interaction of transportation system with land use over time. Watling and Cantarella (2013) summarized the state of the art knowledge in modeling of transportation systems to conduct effective travel demand management and control policies.

1.2 Motivation

It is clear that sustainability analysis of transportation systems requires a broad perspective including various systems, such as the economic, and the political, social, and environmental systems. This perspective enables the consideration of such relevant aspects as biodiversity, human health, quality of life, and life expectancy. Such analysis requires significant amounts of data as well as methods to develop adequate SIs. Although not all data that one may want to use is available, there is a vast amount of relevant information that can be obtained from such organizations as The World Bank, the United Nations, the Bureau of Transportation Statistics, and the U. S. Environmental Protection Agency.

Although fuzzy logic has been used in the context of sustainability to handle key characteristics of the relevant data, its use has not been coupled with a broad perspective considering multiple systems. In addition, important broad effects and the characteristics of the associated data should be explicitly analyzed. Furthermore, previous studies have focused on static techniques to model, analyze, and design effective policies. This research used a system of systems (SOS) (Ackoff, 1971) and a fuzzy logic modeling approach. The SOS includes the Transportation, Activity, and Environment systems. The fuzzy logic modeling approach enables the treatment of the vagueness associated with some of the relevant data. Performance Indices (PIs) are computed for each system using a number of performance measures. In addition, to understand the interdependencies between these PIs, and help make better design and policy decisions at an aggregate level, a suitable modeling approach that captures the dynamic interactions within the SOS is formulated. A method of system of ordinary differential equations is chosen to model the aggregated variables of sustainability and their interdependencies over time. This dissertation incorporates data from the continental United States as well as Las Vegas to study sustainability considerations from both macro-level and micro-level perspective.

1.3 Research Objectives

The following objectives are envisaged: (a) estimation of a sustainability index to analyze the aggregated performance of the overall SOS, (b) seek an understanding of the dynamic relationship between the performance indices and their associated interdependencies, and (c) develop tools that will potentially assist decision makers in long range planning (e.g. prioritize and rank projects, allocation of resources, etc.). In order to achieve the desired objectives, the following steps were proposed.

Step1: A technique is developed that combines multiple performance measures to obtain performance indices. Later, the performance indices are combined to obtain a composite sustainability index. A trend is observed over a period of time that is associated with the economic conditions.

Step 2: The three systems namely: Transportation, Activity and Environment are all interdependent and their performance varies over time. To capture this behavior, a Dynamical modeling approach, such a predator-prey model, is proposed to understand the interdependencies between the three systems. Furthermore, control techniques are used to make investment decisions for policy making.

Step 3: This research developed a framework to estimate performance measures from the traffic characteristics obtained from simulation models. The framework provides an estimate of the benefits and the associated costs to help the decision makers rank and prioritize multiple projects in a timely manner.

1.4 Organization of the Dissertation

The dissertation is divided into six chapters. A layout of the dissertation is represented through flowchart in Figure 1.1. At the macro-level, the proposed research identifies some of the performance measures that are relevant to transportation system, activity system and environment system. Later, the performance measures are combined to obtain performance indices and a composite sustainability index. In addition, the interdependencies between the three systems are studied. Furthermore, the long-term trends of the performance indices are studied and appropriate controls are designed for planning purposes. At the micro-level, a network analysis is done to estimate the performance measures and a benefit-cost analysis is performed to evaluate projects based on long-range planning perspective. This is helpful for decision makers to estimate the benefits of the prospective project improvements as compared to their associated costs.

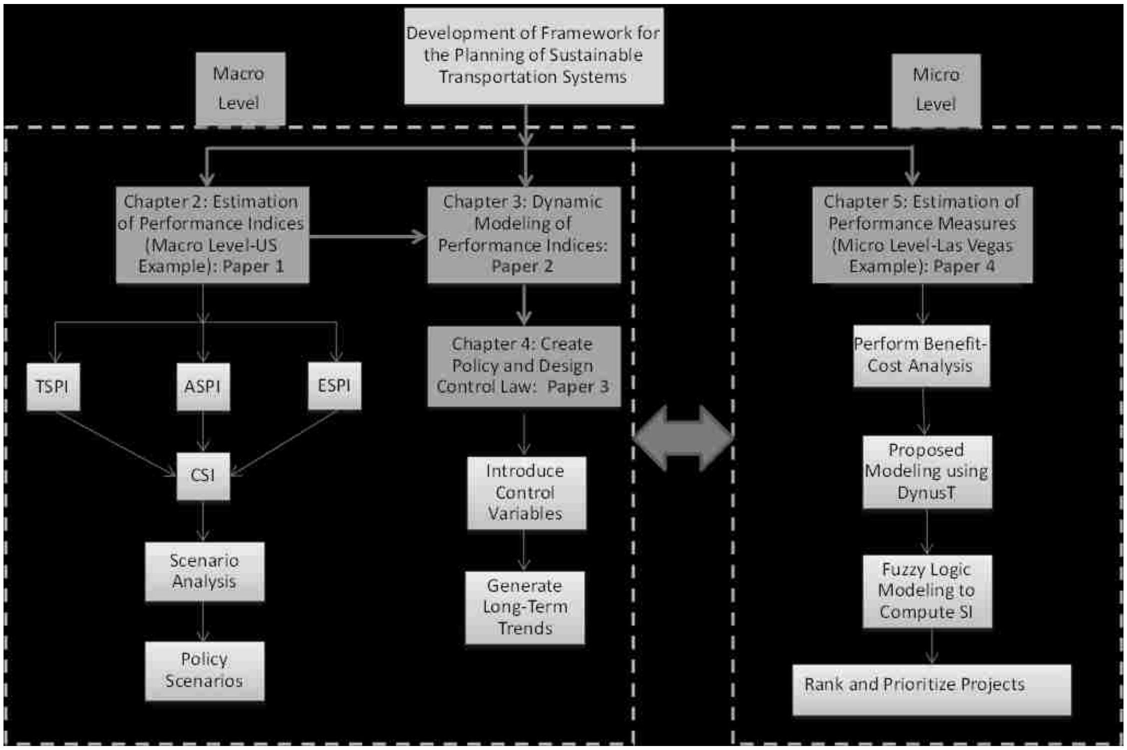


Figure 1.1 Flowchart of the Dissertation

This dissertation follows a manuscript format and starts with this Introduction. Chapter 2 is a manuscript titled "Estimation of Performance Indices for the Planning of Sustainable Transportation Systems". It proposes a system of systems (SOS) and a fuzzy logic modeling approach to study the actual trends over time in terms of system performance and the associated sustainability. The SOS includes the Transportation, Activity, and Environment systems. Performance Indices (PIs) are computed for each system using a number of performance measures. The results showed that the transportation and activity systems follow a positive trend, with similar periods of growth and contractions; in contrast, the environmental system follows a reverse pattern. The results are intuitive and are associated with a series of historic events, such as depressions in the economy as well as policy changes and regulations.

Chapter 3 is a manuscript titled “Dynamic modeling of Performance Indices for the Planning of Sustainable Transportation Systems”. It attempts to build dynamic models to capture the interdependent behavior of transportation, economic, and environmental systems. Non-linear modeling techniques were utilized to capture the nominal behavior of all the three systems. The results indicated periodic behavior with a phase lag for the performance of transportation and the activity system; the performance of environment system decayed with time.

Chapter 4 presents a manuscript titled “Development of Control Models for the Planning of Sustainable Transportation Systems”. It introduces the control variables into the dynamic model presented in Chapter 3. The dynamic model is given by a system of three nonlinear differential equations representing the dynamics of the three independent states; namely transportation, activity, and environmental systems. A policy scenario considering investment in energy efficient technologies and its effects on the states is discussed. Optimal control techniques were used to design the controls. The results showed that it is possible to formulate an optimal control to achieve the desired target. The numerical results were based on actual parameters and were presented to illustrate the long term trends of the states. It is emphasized that the methodology discussed here will be helpful to decision makers to make optimal decisions.

Chapter 5 represents a manuscript titled “Development of a Framework to Evaluate Projects Using Dynamic Traffic Assignment Models”. This chapter investigates a case study in Las Vegas Metropolitan area to rank projects based on sustainability index values. It discusses existing state-of-the-art practices and models, and estimates multiple quantitative (travel time, emissions, crashes, fuel consumption, vehicle operating costs etc.) performance measures using a dynamic traffic simulation model. Furthermore, two techniques were analyzed and a benefit-cost analysis was performed on selected projects. The results indicated that the proposed modeling framework provides an alternate methodology for decision makers to prioritize and rank projects.

Chapter 6 summarizes the overall insights gained from this research, identifies significant contributions, limitations, and discusses potential future research directions.

CHAPTER 2

ESTIMATION OF PERFORMANCE INDICES FOR THE PLANNING OF SUSTAINABLE TRANSPORTATION SYSTEMS

2.1 Introduction

2.1.1 Background

With the rapid increase in economic development throughout the world, there is stress on the resources used to support global economy, including petroleum, coal, silver, and water. Currently, the world is consuming energy at an unprecedented rate never seen before. Based on data from 2005, about 30.6 billion barrels of petroleum are used annually worldwide (EIA, 2006). The estimates indicate that the availability of total world reserves is in the vicinity of 1.3 trillion barrels, and will be depleted by 2047 (MacKenzie, 1995). The finite nature of such non-renewable natural resources as petroleum and coal puts pressure on the environmental system, and ultimately reduces the availability of resources for future generations. Hence, it is critical to develop planning and operational strategies that seek to achieve a sustainable use of existing natural resources.

The development of a sustainable system and its corresponding planning strategies requires an adequate definition of sustainability as well as mechanisms to quantify, qualify, and assess sustainability. The quantification of sustainability poses considerable challenges, ranging from data availability to adequate methods to process information. Numerous studies have established different measures to quantify sustainability (Zheng et al., 2011). According to Bell and Morse (2008), sustainability primarily is measured by means of three components: (i) time scale, (ii) spatial scale, and (iii) system quality. The time and spatial scale correspond to the analysis period and the geographical region of interest, respectively. On the other hand, system quality corresponds to the quantification of the overall system performance or state. In order to quantify system quality, Sustainability Indicators (SIs) have been developed in a diverse range of fields, including biology and the life sciences, hydrology (Sagarika et al., 2014; Kalra et al., 2013; Carrier et al., 2013), and transportation. Harger and Mayer (1996) argued that SIs should be simple, diverse, sensitive, timely, quantifiable, and accessible. Bossel (2001) proposed a system-based approach for developing 21 SIs for environmental characteristics. The approach suggested that a system cannot exist independently, and several external factors can intrude on its boundaries. Some studies argue about the various dimensions associated with sustainability considerations (Jeon et al., 2010; Litman, 2007).

It is clear that a truly sustainable state for a system requires all the relevant interdependent sub-systems/sectors and components, at levels so that the consumption of and the impact on the natural and economic resources do not deplete or destroy those resources. Hence, the assessment of a system state requires a holistic analysis in order to consider all the relevant sectors and impacts. However, existing approaches used to study the sustainability of a transportation system are not comprehensive enough to include key interactions with other systems such as the environment, the economy, and society in general. For example, the current planning of transportation systems is limited in terms of the number, accuracy, length, and approaches used to consider simultaneously important characteristics, including energy consumption, emissions, accidents, congestion, reliability, economic growth, and such social impacts as human health. That is, the existing practices only consider some effects, the estimations are approximate (Paravantis & Georgakellos, 2007), and the analysis period is relatively short, in the order of 30 years (Huzayyin & Salem, 2012). In addition, these effects are synthetized only on the basis of approximated monetary considerations that are unlikely to capture the full extent of the effects, for instance, the financial cost of emissions or greenhouse gases (Litman, 2012; Zolnik, 2012). For example, Zheng et al. (2011) described various system indicators by primarily considering economic aspects. Although the study provided valuable insights about the quantification of the economic domain of transportation sustainability, it is primarily focused on the transportation sector.

Among several studies that focused on different sectors, impacts, and aspects of sustainability, the following key characteristics have emerged as fundamental for a sustainable system:

- Continuity through time (Conway, 1994; Gray, 1991);
- Development of the needs of current generations without compromising the needs of future generations (WCED, 1987);
- Utilization of resources without compromising their health and productivity (Costanza et al., 1992);
- Development that improves quality of life (IUCN, 1991); and
- Assimilation of economic, ecological, social, and bio-physical components of resource ecosystems (Renning & Wiggering, 1997; Munda, 1995).

In terms of the methodologies available to estimate SIs, numerous studies have proposed different approaches. For example, Multi-criteria Decision Making (MCDM) and Analytical Hierarchy Process (AHP) techniques have been proposed to consider multiple criteria and estimate relevant SIs (Zietsman et al., 2006; Islam & Saaty, 2010; Mendoza & Prabhu, 2000; Zimmermann, 2001; Yedla & Shrestha, 2003; Tsamboulas & Mikroudis, 2000; Awasthi & Omrani, 2009). The MCDM approach selects or ranks different predetermined alternatives and is based on making discrete decisions (Zimmermann, 2001). Traditional MCDM techniques assume that the criteria are well-defined, certain (deterministic rather than stochastic), and independent. In reality, the criteria usually involve stochasticity and interdependence. In addition, some aspects in MCDM models are subjective in nature. The weights used in MCDM always include some uncertainty. The basic idea behind the AHP is to convert subjective assessments of relative importance to a set of overall weights or scores. The scale suggested by Saaty (1980) is used to compute the weights, using linear algebra. These weights are the elements in the eigenvector associated with the maximum value of the matrix. The eigenvalue-based method has been criticized by researchers on the grounds of lack of prioritization and consistency (Crawford & Williams, 1985). In addition, there is an issue of rank reversal possibly arising when a new criteria is added. Due to the above reasons, the theoretical foundation of a rigid scale used in the methods is also questionable (Barzilai, 1998). There have been attempts to address some of these limitations. The computation of the weights in MCDM and AHP requires significant amounts of data and a priori or expert knowledge of the system under study. Furthermore, different regions may require different weights to capture local conditions.

Given the complexities, interdependencies, nonlinearities, vagueness, and incomplete information associated with the various factors that are generally involved when considering the sustainability of a system, some studies have adopted concepts from fuzzy set theory for the development of SIs (Yager, 1994; Klir & Yuan, 1995; Silvert, 1997). Awasthi et al. (2011) applied a fuzzy Technique for Order Preference by Similarity to Ideal Situation approach, to evaluate the sustainability of transportation systems using partial or incomplete information. Opricovic and Tzeng (2003) used a fuzzy multi-criteria model to evaluate post-earthquake land use planning. The modeling approach was developed to deal with qualitative or incomplete information. Mendoza and Prabhu (2003) applied fuzzy logic for assessing criteria and indicators for sustainable forest management. In addition, linear aggregation techniques were used to combine multiple indicators. Liu (2007) tried to integrate MCDM and fuzzy logic techniques to evaluate environmental sustainability. The environmental sustainability of 146 countries was calculated, ranked and clustered. The study was extensive in dealing with multiple variables and indicators. However, only the environment aspects of sustainability were evaluated without considering any other SIs related to the transportation or activity system. Similarly, Prato (2005) discussed a fuzzy logic approach for evaluating ecosystem sustainability. Data needs as well as the lack of technical expertise were important issues in this study. Marks et al. (1995) used fuzzy logic techniques to develop a theoretical framework for the evaluation of sustainable agriculture. The study argued about the advantages of fuzzy logic over conventional MCDM techniques. An important characteristic in these studies is their limited scope in terms of the system(s) considered in the analysis.

2.1.2 Motivation

It is clear that sustainability analysis of transportation systems requires a broad perspective including various systems, such as the economic, and the political, social, and environmental systems. This perspective enables the consideration of such relevant aspects as biodiversity, human health, quality of life, and life expectancy. Such analysis requires significant amounts of data as well as methods to develop adequate SIs. Although not all data that one may want to use is available, there is a vast amount of relevant information that can be obtained from such organizations as The World Bank, the United Nations, the Bureau of Transportation Statistics, and the U. S. Environmental Protection Agency.

Although fuzzy logic has been used in the context of sustainability to handle key characteristics of the relevant data, its use has not been coupled with a broad perspective considering multiple systems. To consider, explicitly, important broad effects and the characteristics of the associated data, this study proposes a system of systems (SOS) (Ackoff, 1971) and a fuzzy logic modeling approach. The SOS includes the Transportation, Activity, and Environment systems. The fuzzy logic modeling approach enables the treatment of the vagueness associated with some of the relevant data. Performance Indices (PIs) are computed for each system using a number of performance measures. The PIs illustrate the aggregated performance of each system as well as the interactions among them. The proposed methodology also enables the estimation of a Composite Sustainability Index to summarize the aggregated performance of the overall SOS.

The PIs are calculated with an emphasis on transportation systems, while explicitly considering and calculating the PIs for the other two relevant and affected systems. The PIs are calculated based on multiple performance measures with various degrees of resolution and units. These multi-resolution, multi-unit characteristics are intrinsic to the systems under consideration.

This chapter is organized as follows. Section 2.2 describes three interdependent systems: the Transportation, Activity, and Environmental systems. Section 2.3 summarizes the fuzzy logic methodology used in this study. Section 2.4 provides information about the study region and data. Results and analysis are presented in Section 2.5. Scenario analysis is presented in Section 2.6. Some policy perspectives are illustrated in Section 2.7. Section 2.8 provides conclusions associated with this research. Section 2.9 discusses the limitations and recommendations for future work.

2.2 Interdependent Systems

In the context of sustainability, it is difficult to isolate systems or narrow the analysis to a particular region. Different systems such as Transportation have interdependencies with other systems including the economy and the environment. For example, energy resources, which are part of the environmental system, are required by both the transportation sector and the economy. Hence, any policy or strategy affecting the consumption or production of energy has effects at least on the transportation, the economy, and the environment. This research explicitly considers and defines three major interdependent systems, the transportation system, the activity system, and the environmental system.

2.2.1 The Transportation System

The transportation system includes all the infrastructure facilities, vehicles, operators, and control strategies used to provide transportation services to people and to move products. Thus, the overall transportation system includes all modes of transportation, including highways, transit, and fluvial and air modes. Existing literature uses a number of measures to describe or assess transportation system performance. Lomax et al. (1997) identified several measures of congestion, such as travel time, total segment delay, corridor mobility index, delay ratio, and relative delay rate. The Roadway Congestion Index uses volume and capacity to provide a measure of congestion (Schrank & Thomas, 2009). A Roadway Congestion Index exceeding 1.0 denotes an average congestion level that is undesirable during the peak period. Black (2002) uses principal component analysis to examine the relationships among multiple performance measures, including Vehicle Miles Traveled (VMT), travel time, mobility, crashes, fuel consumption, and emissions. The results indicate that VMT is the single most important factor in the context of sustainability. High VMT values do not necessarily mean high congestion; therefore, similar to the Roadway Congestion Index, VMT needs to be used in conjunction with the corresponding capacity. Thus, VMT per lane mile is a desirable performance measure. Furthermore, Vehicle hours of travel (VHT) is a measure of the number of hours vehicles have driven on a given roadway segment during an average day. VHT is calculated by dividing the segment VMT by the average vehicle speed. In addition, transit passenger miles and the number of intersections per capita can be important performance measures depending on the geographic location. Thus, both the demand and supply side should be taken into account for the selection of performance measure.

The Transportation Service Index (*TSI*) is a performance measure that seeks to quantify the movement of passenger and freight by the for-hire transportation sector (BTS, 2011). This index, which is reported every month, can be used in conjunction with economic indicators to analyze the relationships between the economy and the transportation sector. Another interesting performance measure is the amount of personal money spent on transportation; this includes motor vehicles and parts, gasoline, and such transportation services as transit. The public investment on infrastructure is another important performance measure. Depending on the available data, some or all of the above performance measures can be used to develop the Transportation System PI (*TSPI*). The proposed modeling framework is modular and very flexible to enable the seamlessly incorporation of additional performance measures.

2.2.2 The Activity System

Previous studies have described the activity system as the combination of social, economic, political, and other transactions taking place over time and space (Manheim, 1979; Cascetta, 2009). These transactions create and determine the demand for transportation. For example, changes in such economic policies as gas taxes or VMT fees create changes in the demand for transportation. In this research, the activity system consists of the social, cultural, health-related, and economic/financial aspects. A commonly used indicator for the socio-economic development of any country is its Gross Domestic Product. However, the United Nations Development Program (UNDP) (2010) recommends using the Human Development Index because it incorporates all the basic and necessary dimensions for economic prosperity. This index measures the average achievements in a country by considering: (i) a long and healthy life, or life expectancy; (ii) access to knowledge, or the education index; and (iii) a generous standard of living, measured by gross national income per capita. Life expectancy is the average number of years a child is expected to live, assuming that the mortality rate will remain constant (UNDP, 2010). The Education index includes the average number of years of education received in a lifetime and the expected number of years a child will attend school, assuming constant enrollment rates. The gross national income combines the gross domestic product of a country with its income received from other countries, less similar payments made to other countries. Some of these indices or indicators are used in this study to develop the Activity System PI (*ASPI*).

2.2.3 The Environmental System

The environmental system includes the air, water, soil, and all other natural resources as well as all living organisms that are affected and/or used by the transportation and activity systems. In the United States, data from the Federal Highway Administration and the Environmental Protection Agency suggests that emissions from the transportation system has been reduced drastically over the last 30 years, despite substantial gains in VMT, gross domestic product, population, and employment

(ARTBA, 2011). This has been attributed to the introduction of the Clean Air Act in 1973 and the emergence of fuel-efficient vehicles. However, such other sectors as industrial and chemical have generated increased carbon dioxide emissions over the years, thereby affecting climate change.

The Environmental Sustainability Index (*ESI*) was created by the end of the 1990s by Yale and Columbia Universities (ESI, 2005). This index, which is a single indicator that provides insight into human health and the environment, was promoted by the World Economic Forum. This index currently is considered the most powerful tool available to measure environmental sustainability. The *ESI* uses 76 variables, including air pollution, emissions related to human health, environmental factors, water pollution, and resource minimization. In addition, it incorporates response factors relating to international agreements, such as the preservation of extinct species, limitations to the use of natural resources, limitations to the release of pollutants, and biodiversity conservation.

In 2006, the *ESI* became the Environmental Performance Index (*EPI*). Since then, the *EPI* has been published every two years. The primary constituents of the *EPI* are environmental health and ecosystem vitality. Policy weights used to calculate the *EPI* are approximate percentages that can be summarized as follows: environmental burden of disease, 25%; climate change, 25%; air pollution, 17%; water pollution, 17%; biodiversity and habitat, 4%; forestry, 4%; fisheries, 4%; and agriculture, 4%.

2.3 Methodology

This section provides a detailed framework of the modeling approach used in this study. The concept of Fuzzy Logic was introduced by Lotfi Zadeh in 1965. It is a way of processing data by allowing partial set membership rather than crisp set membership or non-membership (Yager et al., 1987; Tsoukalas & Uhrig, 1997). Fuzzy logic provides a simple and efficient way to arrive at a definite conclusion based upon vague, ambiguous, imprecise, noisy, or missing input information. In the current study, multiple performance measures are combined and corresponding PIs are computed using fuzzy logic for the Transportation, Activity, and Environmental Systems. The PIs are calculated independently for each of the three systems. Their interdependencies are inherent in the data, and are illustrated later in the results and discussion section. Considering a vector of performance measures *X* for system *J* as the inputs, the following three steps are used to calculate the corresponding PI: (1) an inference step, (2) an aggregation step, and (3) a defuzzification step.

2.3.1 Inference Step

The inference step uses "*If-then*" rules and associated membership functions to develop and capture logical relationships between the different performance measures (inputs) and the PI (output).

2.3.1.1 If-then Rules

"*If-then*" rules are logical statements developed based on observation and expert knowledge of the system. The "*if"* part, left-hand side (LHS) or antecedent, is used with the inputs. The "*then"* part, the right-hand side (RHS) or consequent, is related to the output. An example of an "*If-then*" rule is as follows:

If [the VMT per lane mile is High and the Vehicle hours of travel is Medium and the *TSI* is Medium and the personal spending on transportation is Low], then [the *TSPI* is High].

As illustrated in this rule, in order to build the logical relationships between inputs and output, both the LHS and RHS are related to three fuzzy sets, High (H), Medium (M), and Low (L). Table 2.1 shows the set of "*if-then*" rules used in this study to calculate the *TSPI*. Here, four performance measures are used, namely: (i) the VMT per lane mile (*v*), (ii) the vehicle hours of travel (*vht*), (iii) the *TSI*, and (iv) the personal spending on transportation (*ps*) per year. If required, and if the relevant data is available, additional performance measures can be used; the corresponding rules are added to the table. Similar rules have been developed for each of the PIs in order to cover all possible relationships between the chosen system performance measures and the corresponding PI. Thus, the Transportation and Environmental Systems each have four inputs and 81 rules while the Activity System has three inputs and 27 rules.

The rules are based on the rankings from experts in this field. In this research, we have chosen some reasonable rules that allow us to mimic the choice of decision makers. However, fuzzy modeling is subjective, and as a result different experts can have different opinions about their preferences, and hence the rules can differ slightly. Therefore, the results shown here are applicable only to this research and it can vary with different user using same set of inputs and outputs, but the technique is applicable everywhere.

Table 2.1 "*If-then*" Rules for *TSPI*

Rules			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
LHS	*v*	L	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x													
		M																												x	x	x	x	x	x	x	x	x	x	x	x	x
		H																																								
	vht	L	x	x	x	x	x	x	x	x	x																			x	x	x	x	x	x	x	x	x				
		M										x	x	x	x	x	x	x	x	x																			x	x	x	x
		H																			x	x	x	x	x	x	x	x	x													
	TSI	L	x	x	x							x	x	x							x	x	x							x	x	x							x	x	x	
		M				x	x	x							x	x	x							x	x	x							x	x	x							x
		H							x	x	x							x	x	x							x	x	x							x	x	x				
	ps	L	x			x			x			x			x			x			x			x			x			x			x			x			x			x
		M		x			x			x			x			x			x			x			x			x			x			x			x			x		
		H			x			x			x			x			x			x			x			x			x			x			x			x			x	
RHS	*TSPI*		L	L	L	L	L	L	L	L	L	L	L	L	L	L	L	L	L	L	L	L	L	L	L	L	L	L	L	L	L	M	L	M	M	M	M	M	L	M	M	M

Rules			41	42	43	44	45	46	47	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72	73	74	75	76	77	78	79	80	81
LHS	*v*	L																																									
		M	x	x	x	x	x	x	x	x	x	x	x	x	x	x																											
		H															x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
	vht	L															x	x	x	x	x	x	x	x	x																		
		M	x	x	x	x	x																			x	x	x	x	x	x	x	x	x									
		H						x	x	x	x	x	x	x	x	x																			x	x	x	x	x	x	x	x	x
	TSI	L						x	x	x							x	x	x							x	x	x							x	x	x						
		M	x	x							x	x	x							x	x	x							x	x	x							x	x	x			
		H			x	x	x							x	x	x							x	x	x							x	x	x							x	x	x
	ps	L			x			x			x			x			x			x			x			x			x			x			x			x			x		
		M	x			x			x			x			x			x			x			x			x			x			x			x			x			x	
		H		x			x			x			x			x			x			x			x			x			x			x			x			x			x
RHS	*TSPI*		M	M	M	M	M	L	M	M	M	M	M	M	M	M	M	M	H	M	H	H	H	H	H	M	H	H	H	H	H	H	H	H	M	H	H	H	H	H	H	H	H

2.3.1.2 Membership Functions

The quantitative estimation of a PI requires knowledge about the interdependencies between the system performance measures and the corresponding PI. Considering the complexity of the Transportation, Activity, and Environmental Systems, this required knowledge is limited, vague, and sometimes ambiguous. Fuzzy logic provides a mathematical construct to combine all the available knowledge and develop meaningful PI estimates. The "*if-then*" rules are used in conjunction with sets of membership functions to relate the performance measures to the PIs, based on the available knowledge and data. Membership functions are used to define the grade or degree associated with every input and output. In this study, three membership functions are associated with each input and output, as illustrated in Figure 2.1. Triangular membership functions are used in this study because they are easy to define; only three parameters are required: a modal point, the upper width, and the lower width. In addition, due to their conceptual and computation simplicity, triangular fuzzy numbers are commonly used in practical applications (Klir & Yuan, 1995; Pedrycz, 1994; Yeh & Deng, 2004). The domain for the membership functions corresponding to the LHS is defined based on the absolute value of the associated performance measures; the domains for the PIs corresponding to the RHS are normalized so as to use a simple [0, 1] range. Figure 2.1 shows the membership functions for the calculation of the *TSPI.* The LHS denotes the input (performance measures) and the RHS denotes the output (performance index). The units of performance measures on the x-axis are: VMT/lane mile in thousands, TSI in absolute numbers, and personal spending in billions of dollars. Similar functions are defined for the other two PIs.

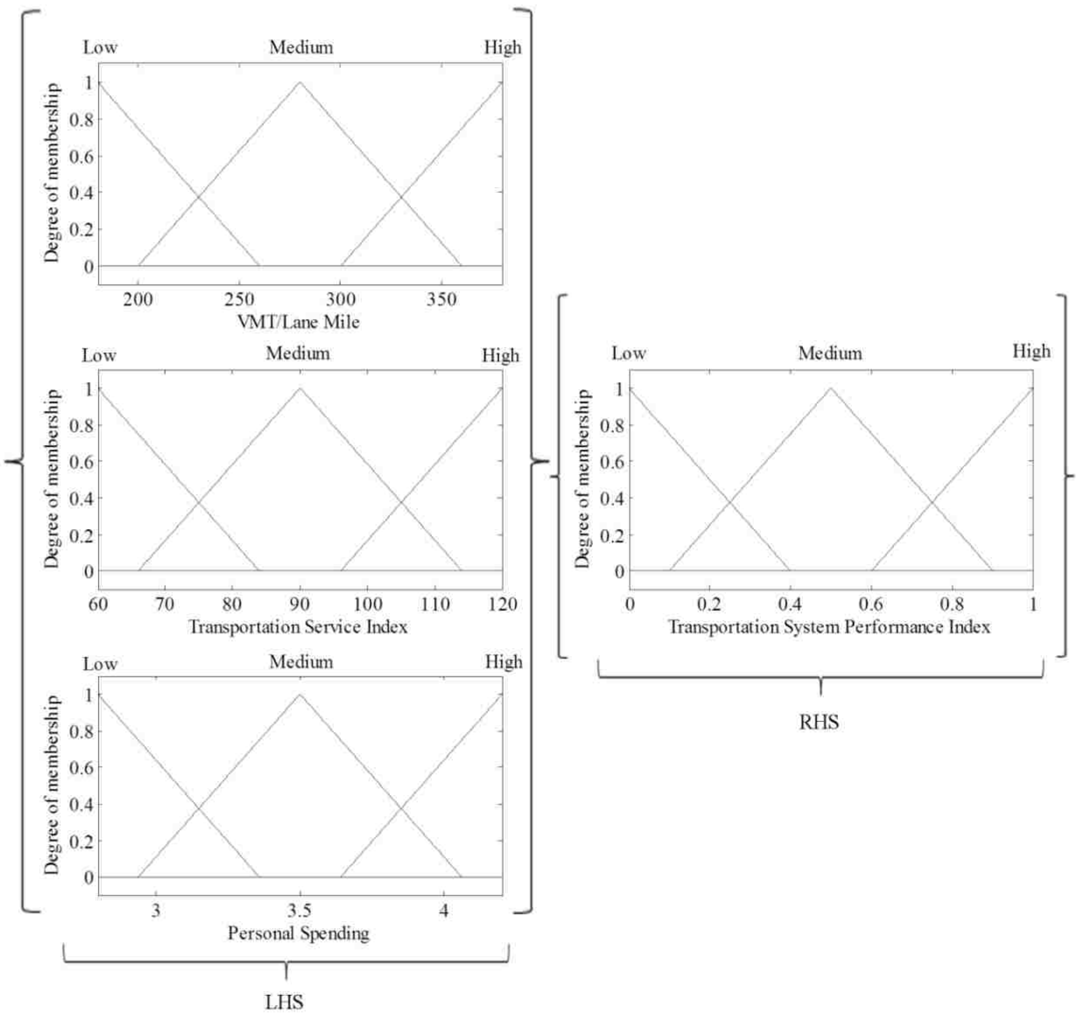


Figure 2.1 Membership functions for the calculation of the Transportation system Performance Index.

Once the "*if-then*" rules and the membership functions are defined, the Mamdani max-min composition operator and the Mamdani min implication operator are used for the fuzzy inference step (Tsoukalas & Uhrig, 1997). For example, the four inputs for the calculation of *TSPI*, *v*, *vht*, *TSI,* and *ps* are matched against the membership functions by using the "*if-then*" rules to determine the degree of activation. The degree at which each rule α is activated (δ^{α}) is obtained by using *v*, *vht*, *TSI,* and *ps* as well as the max-min operator, as shown by Equation 2.1.

$$\delta^{\alpha} = \max_{z \in Z} \min(\mu_{v}{}^{\alpha}(z), \mu_{vht}{}^{\alpha}(z), \mu_{TSI}{}^{\alpha}(z), \mu_{ps}{}^{\alpha}(z)) \tag{2.1}$$

where *Z* represents the universe of domains of the fuzzy sets *v*, *vht*, *TSI*, and *ps*; and μ is a membership function. Equation 2.2 represents the membership functions of the fuzzy outcomes for the *TSPI* obtained, using the min implication operator.

$$\mu_{TSPI^{\alpha *}} = \min(\delta^{\alpha}, \mu_{TSPI^{\alpha}}) \tag{2.2}$$

2.3.2 Aggregation Step

The Aggregation Step represents the aggregation of all the fuzzy output sets obtained after matching all the inputs to the membership functions by using all the "*if-then*" rules. A total of *R* rules for the calculation of *TSPI* are defined. The aggregation step is given by Equation 2.3.

$$\mu_{TSPI^{*}} = \sum_{\alpha=1}^{R} \mu_{TSPI^{\alpha *}} \tag{2.3}$$

2.3.3 Defuzzification Step

The output from the Aggregation Step combines all the available information by using all the defined rules. However, this output needs to be defuzzified to obtain a single crisp value for the corresponding PI, in this case, *TSPI*. The Center of Gravity method (Tsoukalas & Uhrig, 1997), illustrated in Equation 2.4, is used for the Defuzzification Step:

$$TSPI = \frac{\sum_{\alpha=1}^{R} \bar{\theta}^{\alpha} \cdot S(\mu_{TSPI^{\alpha*}})}{\sum_{\alpha=1}^{R} S(\mu_{TSPI^{\alpha*}})} \tag{2.4}$$

where $\bar{\theta}^{\alpha}$ is the centroid of the fuzzy set for the *TSPI*, given by the RHS of rule α; and $S(\cdot)$ calculates the area of the membership function for a fuzzy set.

2.4 Study Region and Data

Sustainability considerations make difficult to isolate systems and narrow the analysis to a particular transportation system or region. It is clear that impacts on the Environmental System, the Activity System, and even the Transportation System extend across regions and boundaries. In addition, the level of resolution of the available data may limit localized analyses. Hence, to illustrate the proposed method, without loss of generality, the United States is used as the study area. Similar analyses can be conducted for other regions and, ideally, the entire globe. In this case, the analysis was conducted for a period of 22 years between 1990 and 2012.

The four performance measures used in the examples in Section 2.3 for the estimation of the *TSPI* in this study were obtained from the Bureau of Transportation Statistics (BTS, 2011). The *ASPI* includes the following performance measures provided by the United Nations (UNDP, 2010):

(i) Gross national income (*gni*);

(ii) The Education Index (*ei*); and

(iii) Life expectancy (*le*).

The Environmental System Performance Index (*ESPI*) is based on the following performance measures:

(i) Carbon dioxide emissions (*ce*) (EIA, 2008);

(ii) Air pollutants (*ap*) (EPA, 2009);

(iii) Water pollutants (*wp*) (World databank , 2010); and

(iv) Energy consumption (*ec*) (EIA, 2011).

Table 2.2 shows the nominal values of performance measures for the Transportation, Activity, and Environment systems respectively.

Table 2.2 Nominal values of performance measures for Transportation, Activity, and Environment Systems

	Transportation System Performance Measures				**Activity System Performance Measures**			**Environment System Performance Measures**			
Year	**VMT/Lane Mile**	**TSI**	**Personal spending**	**VHT**	**Income**	**Education**	**Life Expectancy**	**CO2 Emissions**	**Air Pollutants**	**Energy Consumption**	**Water Pollutants**
	(Thousands)		**(Billions $'s)**		**(Dollars)**	**Index**	**(Years)**	**(Million metric tons)**	**(Million short tons)**	**(Quadrillion BTU)**	**(Kg per day)**
1990	266.34	67.67	.	0.84	34405.58	0.87	75.22	1368.99	254.65	84.65	.
1991	268.56	68.10	.	0.86	34789.06	0.88	75.51	1356.66	245.60	84.61	.
1992	276.60	72.96	.	0.86	35172.54	0.88	75.79	1382.36	238.40	85.96	.
1993	282.38	76.31	.	0.9	35556.02	0.89	76.07	1410.35	233.13	87.60	.
1994	289.52	82.18	.	0.91	35939.50	0.89	76.35	1431.88	231.43	89.26	.
1995	296.98	85.66	2,935	0.93	36322.98	0.89	76.63	1445.94	218.21	91.17	.
1996	305.65	86.42	3,072	0.95	37674.20	0.89	76.91	1496.55	215.76	94.17	.
1997	311.61	91.92	3,235	0.96	39025.42	0.90	77.18	1516.76	203.90	94.76	2,307,022
1998	324.07	97.15	3,436	0.97	40376.63	0.90	77.46	1528.50	200.34	95.18	2,592,730
1999	331.04	100.28	3,644	0.99	41727.85	0.90	77.73	1544.93	195.77	96.81	2,550,845
2000	336.14	100.00	3,718	1.01	43079.07	0.90	78.01	1595.41	193.89	98.97	2,543,653
2001	340.94	97.84	3,788	1.02	42803.20	0.90	78.15	1566.78	183.79	96.32	2,481,637
2002	346.42	99.33	3,856	1.03	42730.34	0.90	78.28	1578.83	186.56	97.85	2,305,847
2003	349.82	101.50	3,937	1.03	43245.75	0.90	78.42	1592.20	179.19	98.13	2,133,051
2004	357.61	108.00	4,004	1.04	44592.62	0.89	78.57	1623.26	171.76	100.31	1,960,254
2005	360.87	110.69	4,001	1.03	45894.11	0.89	78.74	1629.21	163.69	100.44	1,889,365
2006	360.28	110.55	3,920	1.03	46962.71	0.89	78.91	1607.22	153.42	99.79	.
2007	359.06	110.93	3,951	1.03	47213.70	0.89	79.09	1632.50	143.92	101.53	.
2008	351.31	109.95	3,613	0.98	46788.74	0.89	79.27	1585.61	133.30	99.40	.
2009	348.79	100.59	3,442	0.98	45789.79	0.89	79.43	1476.98	137.30	94.72	.
2010	346.14	106.17	3,495	0.99	47093.85	0.89	79.58	1531.72	136.24	98.04	.
2011	343.86	111.1	3,530	0.99	50650.00	0.90	79.70	1492.02	135.97	97.47	.
2012	353.67	112.25	3,565	1.0	52340.00	0.90	79.80	1441.07	132.42	95.10	.

2.5 Results and Discussion

Figure 2.2 shows the normalized performance measures and performance index for the Transportation System. The historic trend for the VMT per lane mile (in thousands) covers a period from 1990 to 2012. It is clear that the trend is increasing except between 1990-1991. This could be attributed to the recession during each of those time periods (Mussa, 1984; Kamery, 2004). During 2005-2006, the VMT started decreasing probably as a consequence of the rising oil prices (Genier, 2008). The trend for the *TSI* covers from 1990 to 2012. The base year for *TSI* = 100 is taken as the Year 2000. The figure shows the decrease in *TSI* between the Years 2000-2002, when the terrorist attack on September 11 occurred. In 2001, there was less freight and passenger travel. Between Years 2008-2012, the financial crisis resulted in a severe recession with consequences on *TSI*, as illustrated in Figure 2.2. Personal spending on transportation is included during 1995-2012. It is evident that spending increases from 1995-2005 as a result of economic development. However, in 2006, spending started decreasing as a result of a rise in gas prices, which hit $4 a gallon. Later, the financial crisis during 2007-2012 resulted in decreased spending for transportation-related activities.

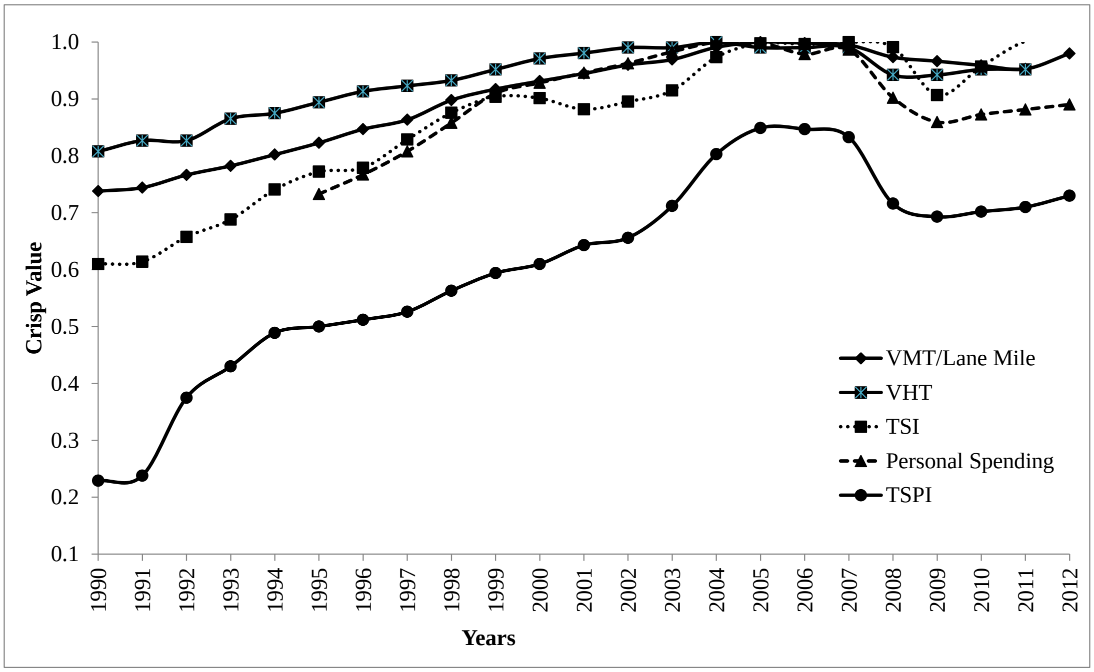


Figure 2.2 Historical Trend of Transportation System Performance Index and its Performance Measures.

Figure 2.2 also shows the historic trend of the Transportation System performance index from 1990 to 2012. The crisp value in the y-axis is obtained by using the fuzzy approach discussed in earlier sections. Here, the closer the *TSPI* to 1, the higher is the performance of the Transportation System; if its value is close to 0, then performance is lower. The crisp values can only be used as a relative measure to compare between alternatives and scenarios. It cannot be used to assess the absolute value of the sustainability of the system. It is evident that *TSPI* has the best value between years 2005-2006, when the economy was booming, and the least value between years 1990-1991. The curve for the *TSPI* follows a pattern consistent with VMT/lane mile and *TSI*. That is, the *TSPI* increases with the increase in VMT/lane mile and TSI. According to Genier

(2008), rising oil prices during 2005-2006 has led to reduced VMT and promoted alternate modes of transportation, such as transit and car-pooling, as well as the use of more efficient vehicles.

Figure 2.3 shows the normalized performance measures and performance index for the Activity System. The trend of the average annual income in Gross National Income per capita is provided from 1990 to 2012. The trend increased, with a high growth rate until 1999. The rate started decreasing in 2000 following the technology bust, also known as the Dot-Com Bubble; and later in 2006, following the housing crisis. It is noted that the rate of growth in income is less in the past decade as compared to earlier decades.

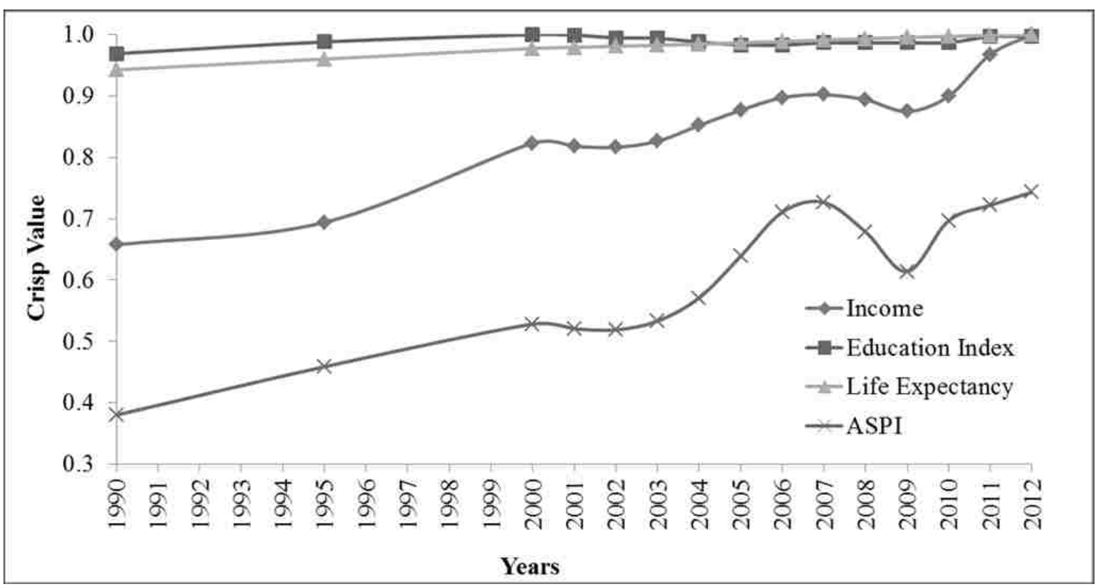


Figure 2.3 Historical Trend of Activity System Performance Index and its Performance Measures.

The trend of the average annual education index is provided from 1990 to 2012. This index started increasing from 1990 to 2000, the primary reason being the invention of new technologies and innovations that kept the United States in the forefront of education. In addition, a new wave of technological revolution was seen in the form of start-ups. Also, science, engineering, and medical disciplines saw a new era of growth and development. The reason for a slight decline in the education index between 2000 and 2004 is not clear yet. The trend of the average annual life expectancy is provided from 1990 to 2012. The average life expectancy has increased from 74 years in 1990 to 80 years in 2012. This increase can be attributed to the technological advancement in medical facilities and billions of dollars spent on research and the development of new and effective drugs.

Figure 2.3 also shows the trend for the Activity System's performance index from 1990 to 2012. This index started increasing from year 1990 until the year 2000 as a result of economic development. Starting with the technology bust in 2000 and terrorist attacks in 2001, the economic activity started to decrease and did not recover until the end of the year in 2003. Since 2003, the Activity System started an upward trend before hitting a peak in 2007. The financial crisis from 2007 to 2009 resulted in a dramatic decrease in economic activity, often compared as equivalent to the Great Depression of 1930s. The year 2009 marks the period of "official recovery" from the recession.

Figure 2.4 shows the normalized performance measures and performance index for the Environmental System. The trend of carbon dioxide emissions is provided from years 1990 to 2012. This is an increasing trend except during 1990-1991, a time of global political unrest and high inflation; 2000-2002, due to the technology bust and September 11 attacks; 2005-2006, due to high gas prices; and 2007-2012, with the financial crisis. The trend of air pollutants is provided from 1990 to 2012. With the introduction of the Clean Air Act in 1973, there has been a dramatic reduction in air pollution. In addition, the introduction of innovative technologies, such as hybrid and battery powered vehicles, have led to reduced air pollution over the years.

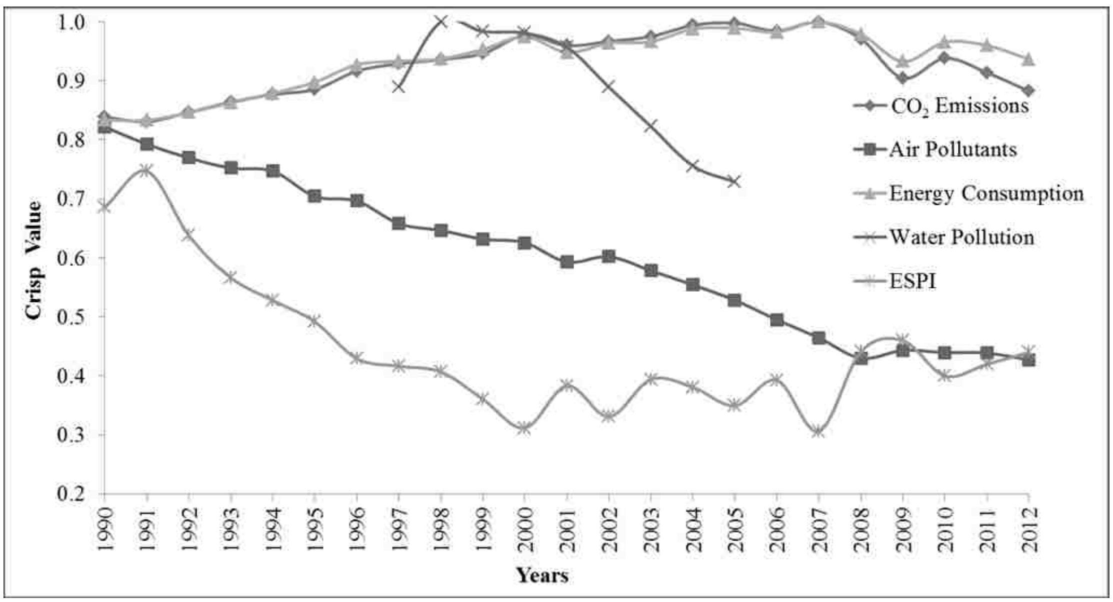


Figure 2.4 Historical Trend of Environmental System Performance Index and its Performance Measures.

The trend for water pollutants is provided from 1997 to 2005. This trend decreases with time as a result of innovative and efficient waste management techniques. The trend for the average annual energy consumption in quadrillion British Thermal Units is provided from 1990 to 2012. This trend indicates that energy consumption decreased during the financial crisis of 1990-1991. After 1991, energy consumption started an upward trend and finally peaked in 2007. However, there were short periods of decline in energy consumption both in 2001, attributed to the September 11 terrorist attacks, and 2006, due to high oil prices. The terrorist attack resulted in decreased travel and less economic activity, while the exorbitant high oil prices promoted the use of new battery-powered and hybrid vehicle technologies.

Figure 2.4 also shows the trend of the Environmental System's performance index from 1990 to 2012. If the value for *ESPI* is close to 1, then the environmental system is excellent; if its value is close to 0, then the system quality is very poor. The best value for *ESPI* occurred during 1990-1995, when economic development was slow as a result of global political unrest and the first gulf war. Since 2000, the quality started to improve, probably as a consequence of multiple periods of economic contractions. Again, the year 2007 marked the beginning of a slight uptrend in the index as a result of a global financial crisis. In general, the environment improves during periods when economic activity is down and/or oil prices are high. In addition, the curve for the *ESPI* follows a pattern consistent with carbon-dioxide emissions and energy consumption. That is, the *ESPI* decreases with the increase in carbon-dioxide emissions and energy consumption.

Figure 2.5 shows the three performance indices from 1990 to 2012. In this figure the Transportation and Activity Systems follow an increasing trend over the years, with similar periods of growth and contractions; on the other hand, the Environmental System follows a reverse pattern. These trends seem intuitive, as growth in the economy and the transportation sectors are expected to happen simultaneously; this growth requires resources from the environment, thereby increasing emissions and energy consumption.

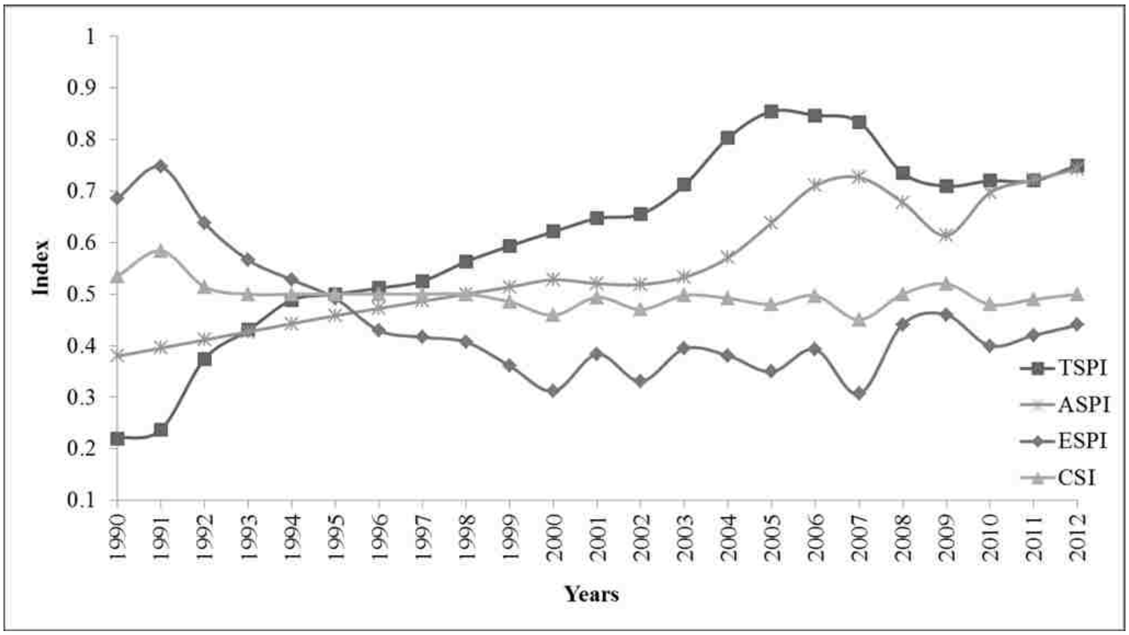


Figure 2.5 Historical Trend of Performance Indices and the Composite Sustainability Index for the Transportation, Activity, and Environmental systems.

Figure 2.5 also illustrates a Composite Sustainability Index (*CSI*), an index used to access the overall sustainability of the SOS used this research. It is calculated using the proposed fuzzy logic approach and the performance index for the Transportation, Activity, and Environmental Systems. The *CSI* shows an overall increasing trend from year 1990 to 1995. However, considering the overall negative slope and corresponding decrease on the *ESPI*, the *CSI* does not continue increasing after 1995 presenting some negative periods and increases only when there is a significant improvement on the *ESPI*.

Based on these observations and the chosen performance measures, negative impacts to the environment seem to be associated with negative consequences on the overall sustainability of the SOS. In general, under the proposed framework, a system is sustainable if the slope of the corresponding PI curve presents a nonnegative slope. Similarly, the overall SOS is sustainable if the slope of the *CSI* is nonnegative. There is a vast literature with similar observations. For example, Young et al. (2007) as well as Lahiri and Yao (2004) have observed that the transportation and activity system follows a lead-lag phase pattern and environment system is inversely related to the other two.

2.6 Scenario Analysis

The techniques described in Section 2.3 were used to combine the transportation system, the activity system, and the environmental system performance indices to obtain the Composite Sustainability Index (*CSI*). As evident in previous sections, transportation system and activity system are supporting the consumption while environmental system is a balancing act. Hence, equal weighting scheme include allocation of 50% for *ESPI* while 25% each for *TSPI* and *ASPI* respectively. This scheme may vary according to the decision maker's preference and geographic region. It is apparent that the graph for *CSI* closely follows the trend for *ESPI*. In addition, the identification and quantification of threshold limit (*TL*) of *CSI* remains a separate research topic, but for demonstration purposes, *TL* is taken as 0.6 in this study. In the context of sustainability, the *TL* of a system is defined as a limit that can be supported by its existing resources without externally sustaining its growth. Figure 2.6 illustrates that the *CSI* shows a decreasing trend from year 1990 to 2012 and the *CSI* lies below the *TL*. For this system to be sustainable the *CSI* trend should be at least above the *TL* and hence appropriate measures and policy recommendations should be adopted to improve its performance.

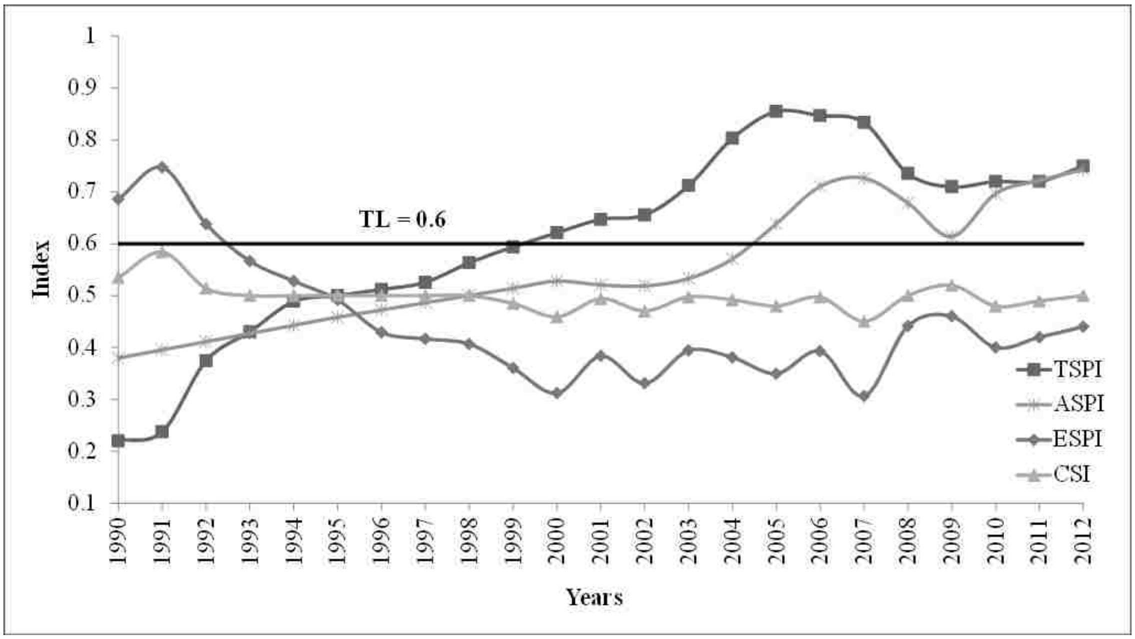


Figure 2.6 Chart showing Threshold Limit and Composite Sustainability Index

As a hypothetical example, Table 2.2 shows various scenarios that can be studied to achieve the pre-specified limits and hence the desired *CSI*. The desired levels of *CSI* are achieved if there is a decrease in *TSPI* and *ASPI*, and increase in *ESPI* in the subsequent years. The best case scenario B states that we can achieve the *TL* with 15 percent reduction in *TSPI* and *ASPI*, and 30 percent increase in *ESPI*. This will ensure reduction in energy consumption and emissions without compromising overall growth and economic development. That is an optimal and optimistic case allowing for decision makers and the authorities to make stringent and corroborate actions to implement necessary policies.

Table 2.3 Scenarios showing effects of *TSPI*, *ASPI*, and *ESPI* on *CSI*

Scenario	*TSPI*	*ASPI*	*ESPI*	*CSI*
A	10% reduction	10% reduction	20% increase	2% increase
B	**16% reduction**	**16% reduction**	**32% increase**	**20% increase**
C	20% reduction	20% reduction	40% increase	54% increase
D	25% reduction	25% reduction	50% increase	72% increase
E	25% reduction	25% reduction	25% increase	10% increase
F	30% reduction	30% reduction	30% increase	15% increase

2.7 Policy Perspectives

This section discusses some policy options for the sustainability of the SOS studied in this research. Some of these options have been implemented in the past revealing some of their effects. Other options are currently under consideration by multiple stakeholders. Figure 2.7 illustrates five policy options that can be used to improve performance and support the sustainability of the SOS considered here.

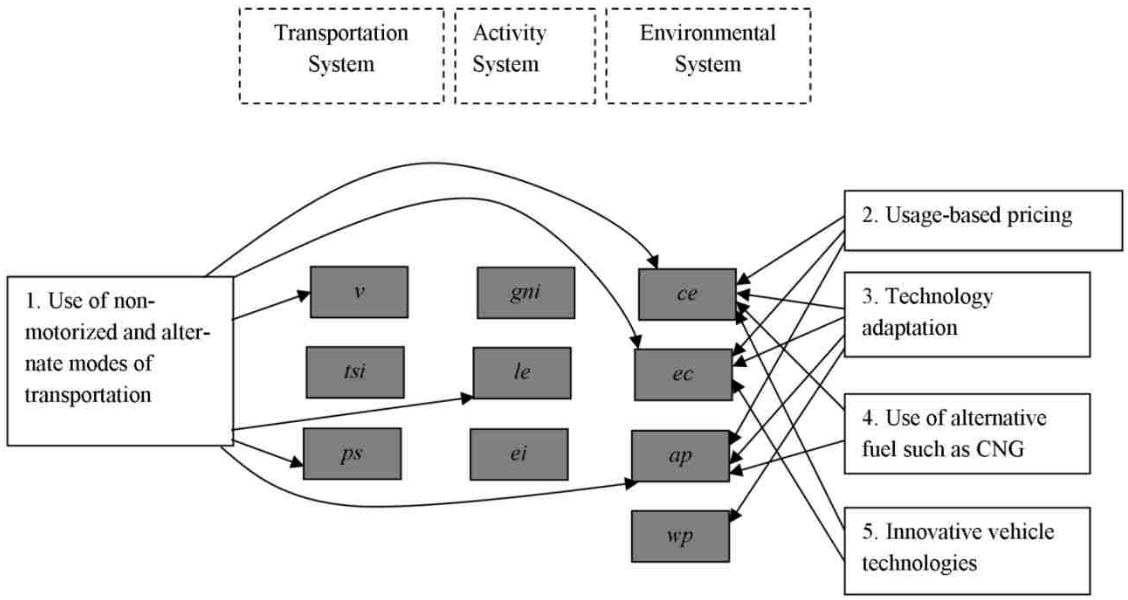


Figure 2.7 Direct effects of policy options on Performance Measures.

The dashed boxes correspond to the three major systems, the grey boxes represent the performance measures within each system, and the suggested policies are depicted by rectangular boxes. These policies have direct and indirect effects on some performance measures and systems. Only the direct effects of the proposed policies are shown through the arrows in Figure 2.7. Conclusion regarding indirect effects will be immature at this point; hence are not discussed here. Each policy is described as follows:

1. Use of non-motorized and alternate modes of transportation. This policy consists of the promotion of non-motorized modes of transportation, such as bicycles, and the use of alternatives for driving alone, such as transit and carpooling. The success of this policy depends on multiple factors, including land use. It may require the establishment of commuter-friendly and transit-friendly development near the central business district. In addition, changes in travel and demand patterns depend on the users' preferences and attitudes as well as convenience. Expected consequences of implementing this policy, among others, include reductions on (i) VMT (Litman & Steele, 2011; Nelson & Nygaard, 2005), (ii) air pollution, (iii) carbon dioxide emissions, (iv) energy consumption, (v) health issues, and (vi) out-of-pocket cost. The money and resources saved can be used to improve such sectors as education and research with further impacts on the gross domestic product.

2. Usage based pricing. Currently, the implementation of a VMT fee is being considered as a viable alternative to replace the current fuel tax for collecting the required resources for highway maintenance (Kim et al., 2002). This policy also can promote the reduction of VMT, along with all the other associated consequences. However, this policy faces a number of deployment as well as acceptance issues.

3. Technology adaptation. The rapid industrialization and technological revolution has resulted in reduced emissions over the years. For example, the use of efficient boilers in coal-fired plants will help reduce carbon dioxide emissions, pollution, and energy consumption (Jordal et al., 2004; Toftegaard et al., 2010). Health related issues will be reduced as a consequence of less pollution.

4. Use of alternative fuels such as compressed natural gas (CNG). The use of alternative fuels in the form of CNG will reduce carbon-dioxide emissions and pollution (Hekkert et al., 2005; Goyal & Sidhartha, 2003). This will lead to a green and cleaner environment (Yeh, 2007) with all the associated benefits to health, the economy, and the quality of life. In the United States, the reserves of natural gas are larger than those of petroleum. Hence, this policy seems plausible from an environmental and economic perspective. The only drawbacks are the time and cost associated with retrofitting vehicles and the supply chain.

5. Innovative vehicle technologies. Replacement of conventionally powered vehicles with hybrid and electric vehicles will reduce carbon-dioxide emissions and nonrenewable fuel consumption (Dresselhaus & Thomas, 2001). Auto makers are particularly interested in this policy (Wirasingha et al., 2008). In addition, the federal government provides tax incentives to develop and manufacture lithium ion batteries in the United States.

Ideally, each of these policies is evaluated before deployment and adoption. Some of them are currently under analysis by multiple agencies and sectors. The proposed framework in this study is descriptive rather than normative. Hence, it can only be used to appreciate the effectiveness and benefits of past policies. Currently, the proposed framework is been extended to enable a normative analysis in order to evaluate potential policy alternatives such as those described earlier.

2.8 Conclusions

Previous studies about sustainable transportation have either focused only on the transportation system, or have not used a methodology that enables the treatment of incomplete, vague, and qualitative information present in the problem context. This study adopted a holistic approach to compute Performance Indices for a SOS including the Transportation, Activity, and Environmental systems. The Performance Indices are synthetized to calculate a Composite Sustainability Index to evaluate the sustainability of the overall SOS. Considering the complexity, vagueness, nonlinearity, qualitative, and incomplete information characterizing the quantification of the Performance and

Composite Sustainability Indices, a fuzzy logic approach was used to calculate these indices. Historic events and policy changes indicated that fuzzy logic provided an adequate approach to estimate both the Performance Indices and the Composite Sustainability Index.

Results of the analysis for the U.S. showed that the Transportation and Activity System both follow a positive trend over the years, with similar periods of growth and contractions. In contrast, the environmental system follows a reverse pattern. This seems intuitive, as periods of economic and transportation growth is expected to have a negative effect on the environment, leading to increased emissions and energy consumption. In general, the performance of the environmental system has decreased significantly over time. Policies adopted to protect the system have shown positive effects. However, the current performance of the Environmental System is questionable, and long-term policies need to be developed.

The conclusions provided here are based on the results obtained using a limited number of performance measures. Adding or removing performance measures are expected to change the results and conclusions. In general, following a holistic approach, it is expected that the more relevant performance measures are used, the more comprehensive and accurate the analysis. Planning and operational policies for the sustainability of the Transportation, Activity, and Environmental systems can be developed using the proposed approach. Considering the current practice of making planning decisions at the regional and jurisdictional level, the framework used in this study is currently been extended to enable the analysis of regional systems including large metropolitan areas. A simulation-based approach is been developed to estimate multiple performance measures required to calculate adequate performance indices.

2.9 Limitations and Recommendations

There are certain limitations associated with this research. This research is preliminary work addressing the direction and movement of performance indices without quantifying the impacts of policy decisions on performance measures. Also, the concept of *TL* is for reference purposes only and its numerical value is not estimated in this study. This computation of *TL* has been estimated and successfully used in various disciplines such as hydrology, geography, ecology etc. However, detailed and thorough analysis is required to estimate the *TL* in the context of sustainability.

Policy recommendations should be based on the public consensus, and appropriate measures should be taken to educate and create awareness among the masses. This will significantly improve the chances of creating suitable polices that are beneficial to the society. The policies should be created based on two aspects: time and cost. In this research, policy 2 and 3 are recommended as they can be implemented easily within timeframe of 2-3 years. In addition, policy 2 is a cost-effective method and the government can immediately start reaping the benefits. In contrast, policies 1, 4 and 5 will require significantly higher time (5-10 years) and cost. As evident, the implementation of policies 4 and 5 will require many years as it takes time to generate resources and create infrastructure. Also, policy 1 will require long range transportation planning to shift or change the land use and create opportunities for transit friendly communities.

To summarize, the study attempts to generate a preliminary framework for sustainable transportation system, and hence the concepts and the performance measures can be modified depending on the geographic region. This requires thorough understanding of the preferences and knowledge, and the involvement of decision makers. Moreover, a much robust analysis can be performed using dynamic modeling or system dynamics, whereby the cause and effect relationships are studied between performance measures and policy recommendations.

CHAPTER 3

DYNAMIC MODELING OF PERFORMANCE INDICES FOR THE PLANNING OF SUSTAINABLE TRANSPORTATION SYSTEMS

3.1 Introduction

In the recent years, sustainability has become a very important research area in the field of transportation. Many studies have focused on understanding the design and analysis of sustainable transportation systems (Cascetta, 2008; Manheim, 1979). Issues that have been discussed include the formulations, analysis, design, and computation of solutions to such problems through the use of appropriate policies, ranging from tolls and tradable pollution permits (Nagurney, 2000). Li et al. (2013) addressed the design of sustainable cordon toll pricing schemes and the findings suggest the interrelationships among cordon toll scheme, traffic congestion, environmental effects, and urban population distribution. The study also revealed the effects of subsidizing the retrofit of old vehicles on reduction in emissions and determined the optimal subsidy policy for social welfare. Szeto et al. (2013) discussed a sustainable road network design and provided interaction of transportation system with land use over time. Watling and Cantarella (2013) summarized the state of the art knowledge in modeling of transportation systems to conduct effective travel demand management and control policies.

Sustainability of supply chains has emerged as a major theme in both research and practice, since the impacts of climate change have made both producers and consumers more cognizant of their decision-making and how their decisions affect the environment.

The study of sustainability and supply chains helps understand how business integrates in context with the environment (Linton et al., 2007). Marale (2012) discussed the dimensions of human life and its linkages with the external environment for sustainable development. In addition, he proposed practical tools to solve global environmental problems. Chiabai et al. (2012) discussed the use of stated preference techniques to evaluate the importance of information and communication technology for environmental sustainability in key sectors (climate change, natural resources, energy, and biodiversity). Kitthamkesorn et al. (2013) used mathematical programming formulations to enhance the environmental sustainability through efficient promotion of ‘go-green’ transportation modes which included public transit and bicycle.

Nguyen and Coowanitwong (2011) discussed the application of strategic environmental assessment tools for sustainable air quality policies. Their study was robust and helped to integrate the environmental aspects into decision making process. In addition, environmental performance can be looked upon as a source of reputational, competitive, and financial advantage among businesses (Miles & Covin, 2000). It is evident that customers and suppliers will punish polluters that violate environmental rules; this is known as a reputational penalty (Klein & Leffler, 1981; Klassen & McLaughlin, 1996). The use of plug in electric vehicles (PEVs) has increased in recent years due to advances in battery technologies, increased gasoline prices, and increased awareness towards the detrimental environmental effects. Chen and Wang (2013) discussed the renewable portfolio standards in the presence of green pricing programs and greenhouse gas emissions trading. He et al. (2013) explored the use of optimal electricity prices at public charging stations for PEVs. The authors coupled the research with road pricing in order to better manage both power distribution and urban transportation networks. Moura et al. (2010) proposed models for transportation of supplies to large public infrastructure works in congested urban areas. Their idea was to minimize the impact on the environment as well as local transportation users. These studies have identified the environment as a major factor in identifying the performance of any sustainable system.

The concept of sustainability in itself is a broad topic, comprising many dimensions and systems. A system of systems (SOS) approach was used by researchers to study the inter-relationships and dependencies between multiple systems (Churchman, 1968; DeLaurentis, 2005; Parker, 2010). The interactions among these systems were evident in economic cycles over time. The concept of economic cycles, also referred to as business cycles, is a theory that attempts to explain changes in economic activity that vary from long-term growth trends. For example, efforts have been made to understand the relationship between the transportation service index (TSI) and the economy (Young et al., 2007). The results from that study suggested that the freight component of the TSI showed a strong leading relationship to the economy. Using dynamic factor models, another study analyzed the business cycle features of the transportation sector (Lahiri & Yao, 2004). The results indicated that the transportation cycles peak ahead of the economic cycles. A one-to-one correspondence between cycles in the transportation sector and the aggregate economy has been identified (Lahiri & Yao, 2006). The transportation sector and the GDP follow similar cyclic behavior with lead-lag phase as shown in Figure 3.1 (Dutzik & Baxandall). In addition, the effects of vehicle miles traveled (VMT) on resource consumption also were studied (Genier, 2008).

Figure 3.1 Historic plot of GDP vs VMT per capita

Several indicators involving the transportation system (TS), activity system (AS), and environmental system (ES) have been developed by a variety of researchers (Zheng et al., 2011; Bell & Morse, 1999; Bossel, 2001; Paz et al., 2013). The indicators provided a necessary tool to understand such systems. The System Dynamics (SD) approach has been useful in understanding the interactions by considering multiple variables and parameters (Ahmad & Simonovic, 2000, 2004, 2006). In order to understand and model the dynamics of system performance, researchers have used the SD approach based on cause-and-effect analysis and feedback loop structures (Wang et al., 2008; Venkatesan et al., 2011 (a), 2011 (b); Ahmad & Prashar, 2012; Moumouni et al., 2014; Qaiser et al., 2011, 2013). In addition, the SD approach was used to analyze the relationship between transportation and land use (Haghani et al., 2003; Pfaffenbichler et al., 2008). However, there is a difference between SD and dynamical systems. SD is primarily focused on the dynamics of system behavior, while dynamical systems study the dynamics of its parts (Ogata, 1998). For example, in the context of our problem, the three elements are TS, AS, and ES. Since the behavior of a system is different from the behavior of its elements, the SD and dynamical systems each have a different purpose (Higgins, 2002).

Recently, efforts have made to establish the performance indices based on performance measures (Paz et al., 2013). The research tried to understand the interactions by using fuzzy logic techniques to combine multiple performance indices. The results showed that the transportation system performance index (TSPI) and the activity system performance index (ASPI) followed an increasing trend over time, while the environmental system performance index (ESPI) followed a decreasing trend. This had been verified by the growth pattern, with changes in economy and environment. The study was robust, and explained the static nature of the problem. In contrast, the interactions among these systems were dynamic in nature and varied with time.

Based on the cited literature and knowledge of the authors, numerous studies have been conducted regarding the principles and applications of dynamical systems in multiple disciplines, including mechanics, thermodynamics, population ecology, epidemics, economic, and population genetics (Luenberger, 1979). In dynamical systems, the present output depends on the past input; the output changes with time if it is not in a state of equilibrium (Ljung & Glad, 1994). Such dynamical systems currently are being used in evolutionary games (Sandholm, 2005; Sandholm, 2011), ecological predator-prey networks (Nagurney & Nagurney, 2011; Nagurney & Nagurney, 2012), optimization based sample identification methods (Raschke et al., 2013), and energy policy modeling frameworks (Woolley et al., 2009). The theory of dynamical systems also is being utilized in neuroscience to model the brain, and is being applied to robotics (Girard et al., 2008). Simple deterministic models capture the essence of the epidemic process, and provide a solid starting point for analysis (Kermack & McKendrick, 1927).

These models improve the general understanding of the behavior of systems, and help make better design and policy decisions at an aggregate level. Hence, it is vital to use a suitable modeling approach that captures the dynamic interactions within the SOS. A method of system of ordinary differential equations is chosen to model the aggregated variables of sustainability and their interdependencies over time. There are many other methods available for modeling of dynamical systems. For instance, we could choose finite state machines, petri nets, cellular automata, partial differential equations etc. or we could also chose stochastic versions of these such as stochastic differential equations, Markov chains, etc. Generally, the researchers choose the appropriate methodology to suit their goals and tasks and also the availability of tools in that methodology. A cellular automaton is also one of such techniques which have been used successfully for modeling many dynamical systems. Generally speaking, cellular automata is used where the system is divided spatially into cells and then the cell properties change based on the dynamics involving interactions between the neighboring cells. It is definitely possible to model sustainability on a geographic area by dividing the space into cells and then apply the cellular automata methodology. As compared to cellular automata modeling and its corresponding simulation, we have chosen our modeling paradigm because it allows mathematical tractability and analysis from a quantitative point of view. However, it would be a great contribution to literature if we develop cellular automata based model for sustainability and also study its mathematical and analytical properties. We hope to pursue this in the future, where it might also be possible to integrate the two techniques. The proposed modeling paradigm allows us to identify equilibrium points, perform stability analysis, and analyze vector field diagrams at a macro perspective. However, the integration of cellular automata with the proposed modeling is possible by selecting a specific geographic region. Therefore, a macro region can be divided into multiple cells (sub-regions) and the properties of the cells change based on the interactions between them. Sustainability of this macro region is partially dependent on its realization at the micro level. Moreover, the sustainability of individual constituents at micro level is useful to achieve robustness in the system by identifying and eliminating the problems at micro level. Hence, it is equally important to perform the analysis from a micro perspective and advance using a bottom up approach.

Therefore, in this study, the dynamic interactions were developed, because they have not been well-defined and analyzed in the existing literature. The primary reason behind the SOS approach is to gain insight into the behavior and modeling of such systems. With this as the motivation, the overall objective of the proposed research is to build dynamic models of performance indices that help to understand the behavior of interdependent systems.

This chapter is organized as follows. Section 3.2 discusses the data used in this study, and Section 3.3 describes the methodology. The results and analysis are summarized in Section 3.4. Section 3.5 discusses the concept of interconnected networks required for decomposition of large scale dynamical systems. Section 3.6 provides conclusions and recommendations.

3.2 Data

The current research incorporates data from the continental United States. The major data set consists of the yearly performance measures ranging from 1990-2010, 21 years in total (Paz et al., 2013). The TS includes the following performance measures: VMT/lane mile, Personal Spending on Transportation, and TSI. The AS includes the following performance measures: GDP/capita, Education Index, and Life Expectancy. The ES includes the following performance measures: Air Pollution, Water Pollution, Energy Consumption, and Carbon-Dioxide Emissions. The data for this research is obtained from such organizations as The World Bank, the United Nations, the Bureau of Transportation Statistics, and the U. S. Environmental Protection Agency. Fuzzy logic provides a simple and efficient way to arrive at a definite conclusion based upon vague, ambiguous, imprecise, noisy, or missing input information. The multiple performance measures are combined using fuzzy logic to obtain the corresponding Performance Indices (PIs). For example, performance measures such as fuel consumption, carbon dioxide emissions, air pollutants, water pollutants etc. are combined to obtain ESPI.

Similarly, relevant performance measures are combined to obtain the TSPI and ASPI respectively. The PIs are calculated independently for each of the three systems. The following three steps are used to calculate the corresponding PI: (a) an inference step, (b) an aggregation step, and (c) a defuzzification step. The reliability of these PIs is verified using the existing trend for the corresponding performance measures. They follow similar patterns with the periods of growth due to economic boom and downturn as a result of political uncertainties, recession, and financial crisis during the past two decades.

The performance measures were chosen based on thorough literature review that takes into account all the dimensions of Transportation, Economic, Environmental and Social systems prevalent within the society. In fact, the framework to compute PIs is modular and can incorporate more performance measures depending on spatial and geographical scenarios. With the increase in number of performance measures, the PIs will definitely change but the overall trend of the all the PIs remains similar.

3.3 Methodology

In this section, a brief description of Lotka-Volterra equations is presented first, followed by a description of the modeling approach used in this study. Lastly, the equilibrium points and phase plots obtained through modeling are discussed.

3.3.1 Theoretical Background on Lotka-Volterra Equations

The predator-prey equation was developed independently by Alfred Lotka (Lotka, 1920) and Vito Volterra (Volterra, 1931), and is often called the Lotka-Volterra model. The equations are a pair of first-order, non-linear differential equations; they cannot be separated from each other and cannot be solved in closed form. They are primarily used to describe the dynamics of biological systems in which two species interact.

The application of predator-prey equations has been documented in various fields, including ecology (Ricklefs, 2001), biology (Elton, 1924; Strogatz, 1995; 1994), psychology (Nowak & Vallacher, 1998), sociology (Felmlee & Greenberg, 1999), and epidemiology (Brauer & Chavez, 2001). One of the most famous examples of such interactions is illustrated by the Canada lynx and snowshoe hare in Canadian forest (Ricklefs, 2001). Other studies showed the fluctuations of lynx and hare populations across Canada (Elton, 1924; Hofbauer & Sigmund, 1998). Also examined is the predator-prey model for the dynamics of ‘love affairs’ between different species (Strogatz, 1995; 1994; Felmlee & Greenberg, 1999). Brauer and Chavez (2001) presented multiple illustrations about mathematical models in population biology and epidemiology. However, less emphasis has been given to the use of predator-prey equations when multiple species are considered.

The simplest models of population dynamics reveal the delicate balance that exists in almost all ecological systems. The earliest predator-prey model was based on sound mathematical principles while making a number of assumptions about the environment and the evolution of predator and prey populations. The underlying assumptions of the predator-prey model are:

(1) The predator population is totally dependent on the prey species as its only food supply,

(2) The prey population has an unlimited food supply, and there is no threat to its growth other than the specific predator,

(3) The rate of change of population is proportional to its size, and

(4) The environment does not change in favor of one species.

In general, a two species i.e. predator (*P*) and prey (*V*), equations are defined as:

Prey model: $$\frac{dV}{dt} = bV - aVP \tag{3.1}$$

Predator model: $$\frac{dP}{dt} = caVP - dP \tag{3.2}$$

In Equation 3.1, *V* is the prey population whose growth is exponential in the absence of predators, with a rate *b*. The predation rate is a constant denoted by *a*. The predation rate is defined as a fraction of the prey population eaten per predator. In Equation 3.2, *P* is the predator population and it decreases with the absence of prey. The constant *d* is defined as predator mortality rate. The constant *c* indicates the conversion efficiency.

As mentioned above, one main assumption in the Lotka-Volterra model includes the dependence of prey on its food supply, i.e. the prey supply is unlimited. Therefore, this assumption is relaxed such that the prey population cannot grow indefinitely. As a result, modifications to the existing model are required. Replacing the Lotka-Volterra model's exponential growth of the prey population by logistic growth with a carrying capacity *K* yields the model as shown in Equation 3.3.

Modified prey model: $$\frac{dV}{dt} = bV\left(1 - \frac{V}{K}\right) - aVP \tag{3.3}$$

3.3.2 Mathematical Modeling

This research seeks to apply the concepts from aforementioned models in the context of sustainability of TS, AS and ES. The proposed model bears a similar resemblance to the classic predator prey equation; albeit a more sophisticated and advanced approach to study the interaction of three species is suggested in this research.

This research focuses on predator-prey models to study the interactions between performance indices and to understand the dynamics of the system under consideration. The basic argument in this research is to ascertain the validity of TS and AS from the perspective of predator prey modeling. Our first assumption is to establish the measures of TS and AS as a valid representation. Since it has been recognized as a valid measure (Paz et al., 2013), it can be safely assumed that they truly represent the current state of the overall system. The second assumption is that there is an implicit relationship between transportation, activity and environment systems. The third assumption is to consider transportation system as prey and activity system as predator in the classic predator prey model. To understand this, the authors tried to look at the economic system from a macro perspective. To support activity system, goods are moved around via transportation. Therefore, inadequate transportation becomes a limitation for growth in economic activity. This can be rephrased as "given a particular state of economic activity, the support by the transportation system is related to its actual utilization". Hence activity system is using transportation and transportation can be taken as prey. This confirms the notion that AS is enhanced by TS. Additionally, in a multi species system as presented, the third species ES can be considered as a prey whereas TS and AS are predators. The predator prey relationship is a complex and bi-level relationship when multiple species are involved. However, this study is an attempt to analyze the relationship when all the three systems TS, AS and ES are present. The fourth assumption in this research is that Environment is already degraded and will keep on degrading with time.

To summarize, in the context of sustainability, TS and AS feed on the ES; in other words, the TS and AS both act as predators and ES becomes a prey. Both consume the existing resources continuously and, ultimately, deplete the ES, thereby creating an imbalance in the ecosystem. The TS sustains increasing pressure by the amount of growth and development throughout the world. Therefore, the AS can be considered as a predator that eats up the TS, which acts as prey to the AS. The dynamic modeling equations for the TS, AS, and ES are:

$$f_1 = \dot{x}_1 = \frac{dx_1}{dt} = a_{11}x_1(1 - b_1x_1) + a_{12}x_1x_2x_3(1 - b_1x_1), \tag{3.4}$$

$$f_2 = \dot{x}_2 = \frac{dx_2}{dt} = -a_{21}x_2(1 - b_2x_2) - a_{22}x_1x_2x_3(1 - b_2x_2), \text{ and} \tag{3.5}$$

$$f_3 = \dot{x}_3 = \frac{dx_3}{dt} = a_{31}x_1x_2x_3 + b_t\frac{dx_1}{dt} + b_a\frac{dx_2}{dt}, \tag{3.6}$$

where $x_3 < 0$ and a_{11}, a_{12}, a_{21}, a_{22}, a_{31}, b_t, b_a, b_1 and b_2 are all parameters that need to be estimated. The parameters b_1 and b_2 are logistic growth parameters for TS and AS, respectively. The variables x_1 , x_2 , and x_3 in Equations 3.4 through 3.6 denote the values TS, AS and ES respectively. The functions $f_1, f_2, and\ f_3$denote the rate of change of TS, AS, and ES with respect to time.

The study is based on the initial assumption that environment is degrading with time and hence a negative value is used to initialize it in the modeling. Equation 3.4 signifies that the rate of TS is directly proportional to transportation, with logistic parameters to limit its growth, and similar observations are seen in the current physical system. The second term attempts to capture the combined effect of activity and environment on transportation. It denotes the interaction of AS and ES on TS. In a physical system, transportation and activity both complement each other, but with the inclusion of environment the overall scenario changes as suggested by incorporating negative values for environment. However for a given state of environment, it is expected to degrade in the near future due to its continuous consumption by transportation and activity systems. Since environment is taken as a negative value, it has been considered in the modeling that the product term is added.

The first term in Equation 3.5 signifies that in the absence of TS and ES, AS will decrease exponentially since there is no transportation of goods, people etc. to sustain AS. Therefore, for a given value of environment, when transportation occurs, it contributes to the overall activity system. As a result, the more degraded the environment the bigger is the rate of change of AS.

Equation 3.6 shows that the ES is already degrading exponentially with time as seen from first term. Intuitively, the TS and AS together have negative impact on the ES. Moreover, faster growth of AS and TS separately results in faster degradation in ES. Therefore, the rate of decay in ES will be governed by the rate of change of TS and AS, as denoted by the second and third terms in Equation 3.6.

A python script for the above three ordinary differential equations (ODE) is written, and the parameters are calculated using an initial estimate. The parameter values obtained were $a_{11} = 0.11, a_{12} = 1, a_{21} = 1.76, a_{22} = 16, a_{31} = 0.01,\ b_t = 0.01, b_a = 0.01, b_1 = 1, b_2 = 1$.

In order to validate and observe the inherent behavior of three systems, the best fit curves for TS, AS, and ES were evaluated using nonlinear, non-parametric techniques. The nonlinear techniques, such as curve fitting or regression, might be an appropriate choice, based on the initial examination of the data points (Pulugurtha et al., 2006; Maheshwari, 2005). The basic approach to curve fitting depends on the intended goal. In many cases, the goal is simple, and one need not care about regression models and the interpretation of their best-fit values. Curve fitting is the process of constructing a curve, which is best fit through a set of data points, subject to some constraints. The results of curve fitting are discussed in Section 3.4.

The initial value of TS, AS, and ES for the year 1990 was used to initiate the ODE (Paz et al., 2013). From a generalized perspective, the modeling was done for a longer time period. Although Figure 3.2 shows the trends for all three systems for a period of approximately 160 years, it does not imply a relative scale among the three systems. The x axis shows the time period in years starting from year 1990, whereas the y axis denotes metrics for TS, AS and ES. The dashed curve and the dotted curve indicate the TS and AS, respectively. It is evident that the AS peak is followed by the TS peak. Both systems have been steadily decreasing over time as a result of the continued exhaustion of natural resources. The solid curve indicates the ES, and also is decreasing gradually with time. This is due to the continuous appetite for natural resources needed to support economic development and infrastructure facilities.

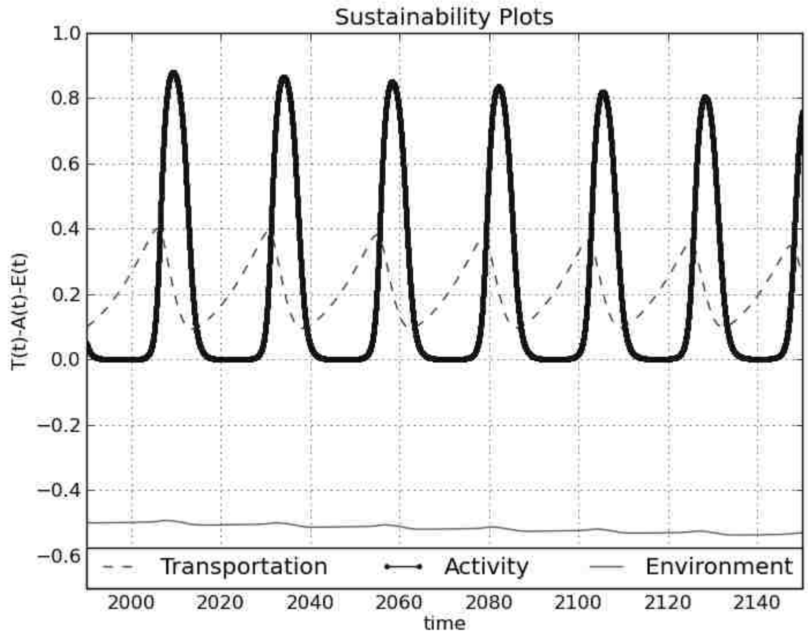


Figure 3.2 Sustainability Plots for the transportation system (TS), activity system (AS), and the environmental system (ES).

Figure 3.3 shows a three-dimensional plot for system evolution for the TS, AS, and ES. The values along the three axes denote their individual metrics. The graph starts when the TS and AS are at the lowest point, and the ES is at a peak. Furthermore, the decay in ES over time is clearly visible from the plot. The description and analysis of the equilibrium points are discussed in Section 3.3.3.

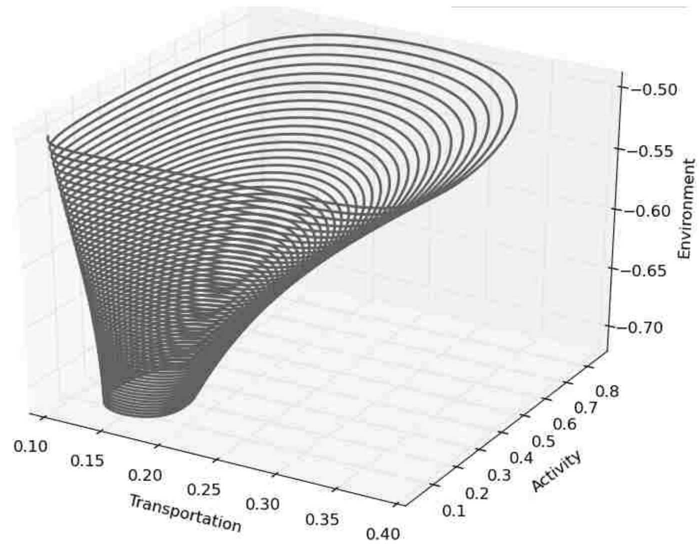


Figure 3.3 System evolution for TS, AS, and ES.

3.3.3 Equilibrium Points

This section describes the dynamics of the interdependent systems. In the usual scenario, the AS thrives when there are adequate TSs. However, after some time, the economic growth becomes enormous in order to keep up with the infrastructure facilities, and ultimately it starts deteriorating. Diminishing economic levels result in an increase in the availability of transportation facilities. These dynamics continue in a cycle of growth and decline.

The equilibrium points for the system of Equations 3.4 through 3.6 are as follows. There are five equilibrium points, namely, $X_1, X_2, X_3, X_4,$ and X_5. The equilibrium points are identified so as to perform the stability analysis. This enables understanding the behavior of the system around a fixed point. A slight perturbation can lead an equilibrium point from stable to unstable, and vice-versa. The equilibrium points of the system developed in this study are shown in Equations 3.7 through 3.11. However, to understand this system, the trivial equilibrium point is obtained by taking $x_1 = 0,\ x_2 = 0$ and $x_3 = 0,$, as shown in Equation 3.7.

$$X_1 = (0,0,0) \tag{3.7}$$

Other equilibrium points are shown in Equations 3.8 through 3.11 for a particular value of x_3. X_2 and X_3 are obtained by equating $\dot{x}_1$ and $\dot{x}_2$ to zero and solving them simultaneously. X_4 is obtained by equating $\dot{x}_1$ to zero, taking $x_2 = 0$. X_5 is obtained by equating $\dot{x}_2$ to zero, taking $x_1 = 0$.

$$X_2 = \left(-\frac{a_{21}}{a_{22}x_3}, -\frac{a_{11}}{a_{12}x_3}, x_3\right) \tag{3.8}$$

$$X_3 = \left(\frac{1}{b_1}, \frac{1}{b_2}, x_3\right) \tag{3.9}$$

$$X_4 = \left(\frac{1}{b_1}, 0, x_3\right) \tag{3.10}$$

$$X_5 = \left(0, \frac{1}{b_2}, x_3\right) \tag{3.11}$$

The Jacobian matrix and the corresponding description of the partial derivatives for the underlying model are shown in Equations 3.12 through 3.21.

$$J = \begin{pmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} & \frac{\partial f_1}{\partial x_3} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} & \frac{\partial f_2}{\partial x_3} \\ \frac{\partial f_3}{\partial x_1} & \frac{\partial f_3}{\partial x_2} & \frac{\partial f_3}{\partial x_3} \end{pmatrix} \tag{3.12}$$

where,

$$\frac{\partial f_1}{\partial x_1} = (a_{11} + a_{12}x_2x_3)(1 - 2b_1x_1) \tag{3.13}$$

$$\frac{\partial f_1}{\partial x_2} = a_{12}x_1x_3(1 - b_1x_1) \tag{3.14}$$

$$\frac{\partial f_1}{\partial x_3} = a_{12} x_1 x_2 (1 - b_1 x_1) \tag{3.15}$$

$$\frac{\partial f_2}{\partial x_1} = -a_{22} x_2 x_3 (1 - b_2 x_2) \tag{3.16}$$

$$\frac{\partial f_2}{\partial x_2} = (-a_{21} - a_{22} x_1 x_3)(1 - 2b_2 x_2) \tag{3.17}$$

$$\frac{\partial f_2}{\partial x_3} = -a_{22} x_2 x_1 (1 - b_2 x_2) \tag{3.18}$$

$$\frac{\partial f_3}{\partial x_1} = a_{31} x_2 x_3 + b_t \frac{\partial f_1}{\partial x_1} + b_a \frac{\partial f_2}{\partial x_1} \tag{3.19}$$

$$\frac{\partial f_3}{\partial x_2} = a_{31} x_1 x_3 + b_t \frac{\partial f_1}{\partial x_2} + b_a \frac{\partial f_2}{\partial x_2} \tag{3.20}$$

$$\frac{\partial f_3}{\partial x_3} = a_{31} x_2 x_1 + b_t \frac{\partial f_1}{\partial x_3} + b_a \frac{\partial f_2}{\partial x_3} \tag{3.21}$$

Inserting the equilibrium points into the Jacobian matrix yield the following eigenvalues. The first equilibrium point in Equation 3.7 yields the Jacobian matrix as shown in Equation 3.22. The corresponding eigenvalues are given by Equation 3.23.

$$J = \begin{pmatrix} a_{11} & 0 & 0 \\ 0 & -a_{21} & 0 \\ b_t\, a_{11} & -b_a a_{21} & 0 \end{pmatrix} \tag{3.22}$$

$$\lambda = a_{11}, -a_{21}, 0 \tag{3.23}$$

The second equilibrium point in Equation 3.8 yields the Jacobian matrix, as shown in Equation 3.24. The corresponding partial derivatives are given by Equation 3.25 through 3.31.

$$J = \begin{pmatrix} 0 & \frac{\partial f_1}{\partial x_2} & \frac{\partial f_1}{\partial x_3} \\ \frac{\partial f_2}{\partial x_1} & 0 & \frac{\partial f_2}{\partial x_3} \\ \frac{\partial f_3}{\partial x_1} & \frac{\partial f_3}{\partial x_2} & \frac{\partial f_3}{\partial x_3} \end{pmatrix} \tag{3.24}$$

where:

$$\frac{\partial f_1}{\partial x_2} = a_{12}\left(-\frac{a_{21}}{a_{22}} - \frac{b_1}{x_3}\left(\frac{a_{21}}{a_{22}}\right)^2\right) \tag{3.25}$$

$$\frac{\partial f_1}{\partial x_3} = \frac{a_{21}}{a_{22}}\frac{a_{11}}{x_3^2} + \frac{b_1}{x_3}\frac{a_{11}}{x_3^2}\left(\frac{a_{21}}{a_{22}}\right)^2 \tag{3.26}$$

$$\frac{\partial f_2}{\partial x_1} = \frac{a_{22}a_{11}}{a_{12}} + a_{22}\frac{b_2}{x_3}\left(\frac{a_{11}}{a_{12}}\right)^2 \tag{3.27}$$

$$\frac{\partial f_2}{\partial x_3} = -\frac{a_{21}}{a_{12}}\frac{a_{11}}{x_3^2} - a_{21}\frac{b_2}{x_3}\left(\frac{a_{11}}{a_{12}x_3}\right)^2 \tag{3.28}$$

$$\frac{\partial f_3}{\partial x_1} = -\frac{a_{31}a_{11}}{a_{12}} + b_a\frac{\partial f_2}{\partial x_1} \tag{3.29}$$

$$\frac{\partial f_3}{\partial x_2} = -\frac{a_{31}a_{21}}{a_{22}} + b_t\frac{\partial f_1}{\partial x_2} \tag{3.30}$$

$$\frac{\partial f_3}{\partial x_3} = -\frac{a_{31}a_{11}a_{21}}{a_{12}a_{22}x_3^2} + b_t\frac{\partial f_1}{\partial x_3} + b_a\frac{\partial f_2}{\partial x_3} \tag{3.31}$$

To comment on the stability of the system, one needs to compute the eigenvalues and relate the stability based on the sign of real part. However, there is an alternate method where we assume the pseudo equilibrium for the system (in the neighborhood of x_3). It can be explained through the following steps.

(1) Assume change in x_3 to be negligible for the period of analysis. In other words, x_3 is treated as a constant.

(2) Reduce the Jacobian matrix accordingly (a 2x2 matrix).

(3) Compute eigenvalues and comment on stability at the equilibrium point.

Using this approach, the system can be visualized as a two species system. The Jacobian matrix at the equilibrium point X_2 is shown in Equation 3.32.

$$J = \begin{pmatrix} 0 & \frac{\partial f_1}{\partial x_2} \\ \frac{\partial f_2}{\partial x_1} & 0 \end{pmatrix} \tag{3.32}$$

This results in the following eigenvalues in Equation 3.33.

$$\lambda = \pm\sqrt{\frac{\partial f_1}{\partial x_2} . \frac{\partial f_2}{\partial x_1}} = \pm\sqrt{-a_{11}a_{21}\left(1 + \frac{b_1}{x_3}\frac{a_{21}}{a_{22}}\right)\left(1 + \frac{b_2}{x_3}\frac{a_{11}}{a_{12}}\right)} \tag{3.33}$$

As a result, the equilibrium point will be a center if λ is real. From Figure 3.5, Figure 3.6, and Figure 3.7, it is evident that if x_3 is constant, then transportation and activity will follow limit cycle behavior. However, when x_3 starts to shift, equilibrium point X_2 follows a trajectory and this shift causes the current limit cycle to change as shown in Figure 3.4. The physical interpretation of the analysis implies that change in value of environment disturbs the maximum potential use of transportation which eventually affects the maximum value of activity. These results are in compliance with the expected behavior.

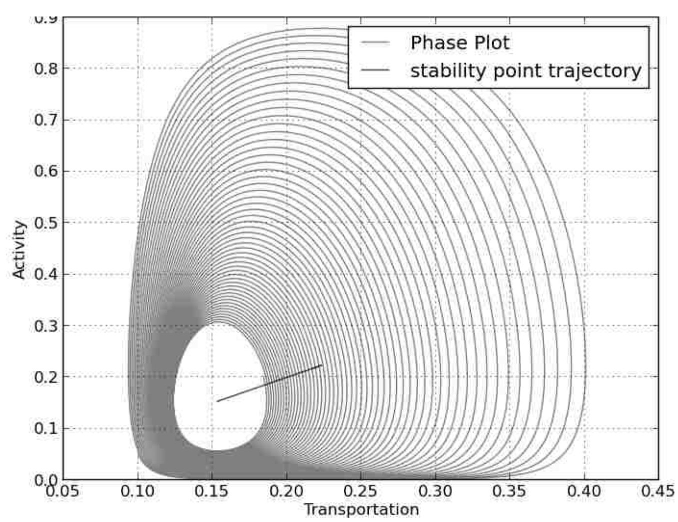


Figure 3.4 Phase plot for multiple ES values

The remaining equilibrium points are the result of introducing logistic parameters b_1 and b_2, which are used to define the boundary of phase plots and their maximum limits. As a result, they do not have any physical significance associated with them; therefore, their analysis is not required at this point. The eigenvalues corresponding to the equilibrium points can be stable or unstable, depending on the values of the parameters. The eigenvalues dictate the qualitative behavior of the system around the equilibrium points.

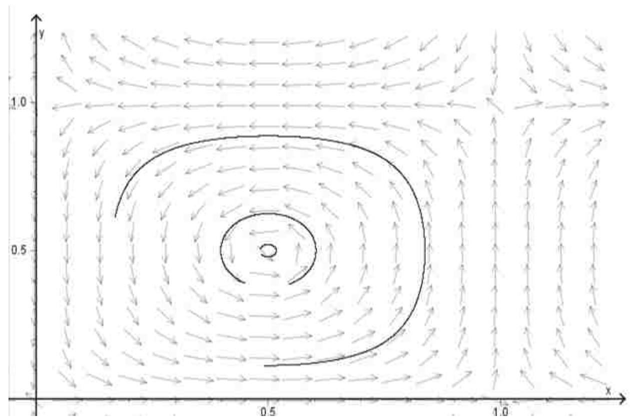


Figure 3.5 Vector field diagram of TS and AS in pseudo-equilibrium for ES = -0.5

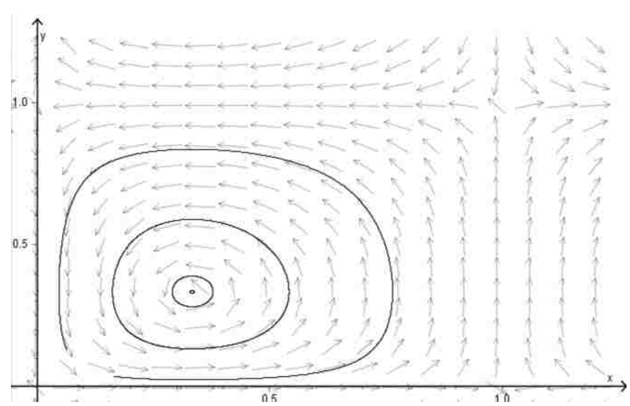
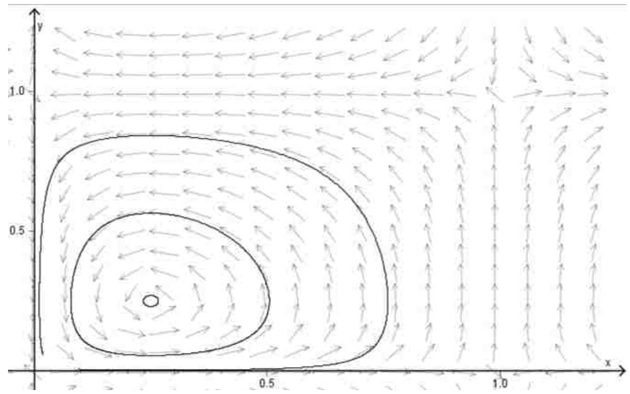


Figure 3.6 Vector field diagram of TS and AS in pseudo-equilibrium for ES = -0.75



(c)

Figure 3.7 Vector field diagram of TS and AS in pseudo-equilibrium for ES = -1.0

Figure 3.4 shows the phase plot for the equilibrium points obtained after the modeling process at various values of ES. The *x* axis and *y* axis indicate the values of TS and AS, respectively. This plot shows the model's performance by assuming pseudo-equilibrium over TS and AS for a slowly varying value of ES. The plot indicates that this equilibrium always shifts and travels along a straight line. As a result, the system tries to reach an equilibrium point, but ultimately cannot attain it. In addition, the behavior of this pseudo-equilibrium is similar to the Lotka-Volterra model.

Figure 3.5, Figure 3.6 and Figure 3.7 shows the vector field diagram of TS and AS in pseudo-equilibrium. A vector field in the plane can be defined as a collection of arrows with a given magnitude and direction, each attached to a point in the plane. The *x* axis and *y* axis indicate the values of TS and AS, respectively. These figures also shows the shift in the equilibrium point (X_2) for various values of ES. As evident from Figure 3.5, Figure 3.6 and Figure 3.7, the equilibrium points X_1,X_3,X_4 and X_5 represent the boundary indicated by logistic parameters. It can be safely concluded that the control over this model is possible, as the equilibrium point X_2 is moving slowly by changing the values of ES.

3.4 Results and Analysis

This section shows the best-curve fit for TSPI, ASPI, and ESPI, respectively. A closer look through the original trend suggests that there is some cyclic and periodic behavior in all the three performance indices (Figure 3.8). Therefore, a linear curve fit is not an appropriate choice. As a result, higher degree polynomials are constructed to appropriately follow the existing trends. A python script is written to get the best-fit curve for TSPI, ASPI, and ESPI, respectively.

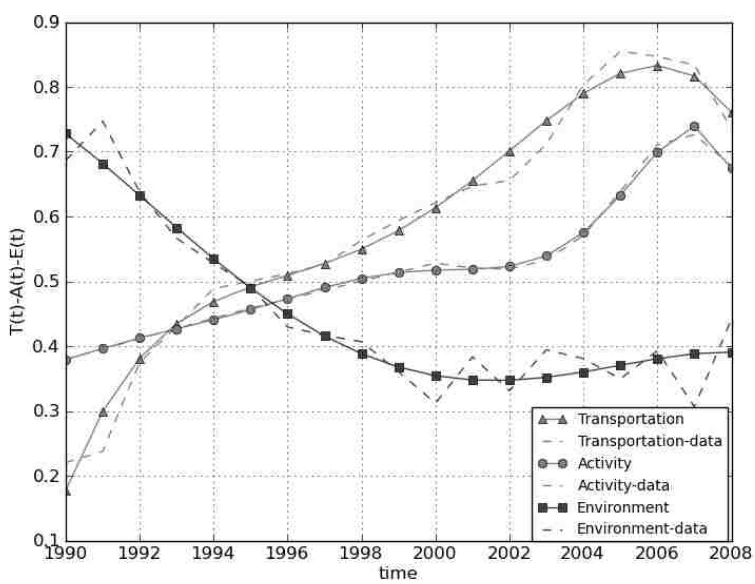


Figure 3.8 Curve fitting plots for TSPI, ASPI, and ESPI.

Figure 3.8 shows the polynomial curve fit for TSPI, ASPI, and ESPI from year 1990 to year 2008. The *x* axis represents the time in years and the *y* axis represents the values of performance indices. The dashed curve represents the original TSPI trend, while the solid triangle curve shows the best curve fit. The best-curve fit model for TSPI is given by Equation 3.34. The dashed curve represents the original ASPI trend, while the solid circle curve shows the best-curve fit. The best-curve fit model for ASPI is given by Equation 3.35. The dashed curve represents the original ESPI trend, while the solid rectangle curve shows the best curve fit. This is an unusual scenario whereby the ESPI follows a periodic pattern, depending on the state of the TSPI and the ASPI. As a result, exponential decay and polynomial functions are used to estimate the best-fit curve. The best-curve fit model for ESPI is given by Equation 3.36.

The Transportation polynomial:

$$x_1 = -6.066 * 10^{-5}x^4 + 0.00219\,x^3 - 0.02607\ x^2 + 0.1461\,\mathrm{x} + 0.1768 \qquad (3.34)$$

The Activity Polynomial:

$$x_2 = -9.376 * 10^{-8}x^7 + 4.704 * 10^{-6}x^6 - 8.754 * 10^{-5}x^5 + 0.0007502\ x^4 - 0.002988\ x^3 + 0.004654\ x^2 + 0.01451\ \mathrm{x} + 0.3793 \qquad (3.35)$$

The Environmental polynomial:

$$x_3 = -1.475 * 10^{-5}x^4 + 5.120 * 10^{-4}x^3 - 3.394 * 10^{-3}x^2 - 2.104 * 10^{-2}\,\mathrm{x} + .1198 + e^{-0.497-0.037x} \qquad (3.36)$$

The aforementioned curve fitting models dictate certain patterns. The proposed mathematical modeling aims to draw upon the understanding of behavior observed in the curve fitting models. Finally, the proposed model is used to understand the dynamics of our interdependent systems. The model can articulate about the performance of SOS for a limited period of time.

Figure 3.9 shows the dynamics of the three systems for a time period of approximately 30 years, starting with year 1990. The *x* axis represents the time in years and the *y* axis represents the normalized values of performance indices obtained after modeling. The TS (dashed curve) and the AS (dotted curve) follow a periodic pattern with a phase lag, whereas the ES (solid curve) follows a decreasing pattern. The results can be verified with the Great Recession from 2008 to 2009, during which time economic activity started deteriorating. As evident, the ES is at lowest point when TS and AS are at near-peak levels. Overall, the ES follows a decreasing trend over time.

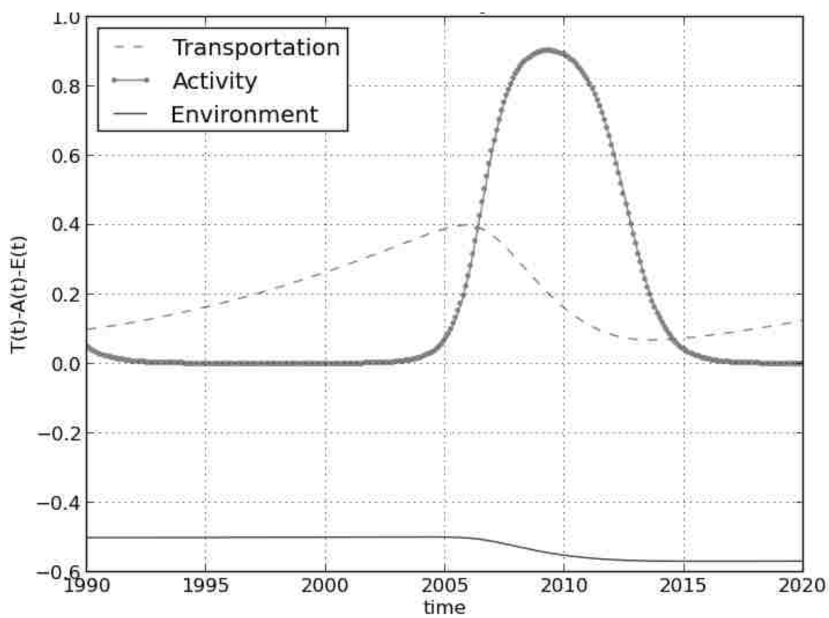


Figure 3.9 Dynamics of TS, AS, and ES.

3.5 Interconnected Networks

The above mentioned dynamic modeling is performed at a macro level by considering United States as an example. This approach gives the decision maker an idea of the dynamic interdependencies between the TS, AS and ES over time. Additionally, the technique presented here provides a hierarchical way on the desired level (micro or macro). However, it becomes equally necessary to disintegrate the region into multiple sub-regions and analyze them separately. Furthermore, it is helpful to analyze the system with a higher resolution to precisely understand the trade, transportation and economic growth that affects the sub-regions. As a result, it becomes important to analyze and prepare a framework that takes into account interdependencies between multiple sub-regions. For example, consider the tri-city area of Las Vegas, Los Angeles and San Diego. All the three sub-regions affect each other with respect to emissions, energy consumption, freight transportation (as a result of ports in Los Angeles and San Diego), economic activity (tourism) etc. Additionally, abundant sub-region data is readily available from local municipalities and counties. This can help to understand the interdependencies between sub-regions. This section discusses a generalized framework that relates the proposed modeling approach with the concept of interconnected networks.

The concepts derived from interconnected networks can be applied to network analysis. The interconnected networks comprise of multiple nodes having diverse states and physical systems. It is well documented that the decomposition principle can be utilized to decompose certain complex systems made of interacting elements into lower dimensionality subsystems (Himelblau, 1973). Each of the pieces within the system is then analyzed individually. Lastly, each individual solution of a particular subsystem can be combined together to obtain an overall solution for the system. If the system represents a structure of subsystems (interconnected elements) having physical meaning, then breaking the interconnections during the analysis can lead to numerical simplifications of the system; this provides further information regarding the structural properties (Siljak, 1978). Using this concept, the current research breaks the system and then investigates its connective structural characteristics.

Let's take an example of a linear constant system S given by Equation 3.37:

$$\dot{y} = Ay \tag{3.37}$$

where $y = (y_1, y_2, \dots \dots y_n)^T$ is the state vector and $A = (A_{ij})$ is a constant $n * n$ system matrix. Equation 3.37 can be rewritten to form Equation 3.38.

$$\begin{bmatrix} \dot{y_1} \\ \dot{y_2} \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} \tag{3.38}$$

Equation 3.38 shows in detail the dependencies of individual components inside the system. As evident, two vector equations can be formulated using Equation 3.39.

$$\dot{y_1} = A_{11}y_1 + A_{12}y_2 \tag{3.39}$$

$$\dot{y_2} = A_{21}y_1 + A_{22}y_2$$

Now, if state vectors y_1, y_2 describe the two subsystems S_1 and S_2, then Equation 3.40 describes the decoupled subsystems, whereas $A_{12}y_2,\ A_{21}y_1$ represent the interactions between the two subsystems.

$$\dot{y_1} = A_{11}y_1 \tag{3.40}$$

$$\dot{y_2} = A_{22}y_2$$

Figure 3.10 shows the weighted directed graph, or digraph, for the interconnected system described by means of Equation 3.39.

[redacted]

Figure 3.10 Weighted digraph.

The aforementioned ideas are extended to introduce the concept of a multi-city network. Figure 3.11(a) shows the interconnected system diagraph for two cities (subsystems) S_1 and S_2. Each subsystem is associated with properties defined by h and p which together constitute the state of the subsystem. As a result, a system of two communities S_1 (h_1, p_1) and S_2 (h_2, p_2) respectively can be represented through the system digraph as shown in Figure 3.11(a).

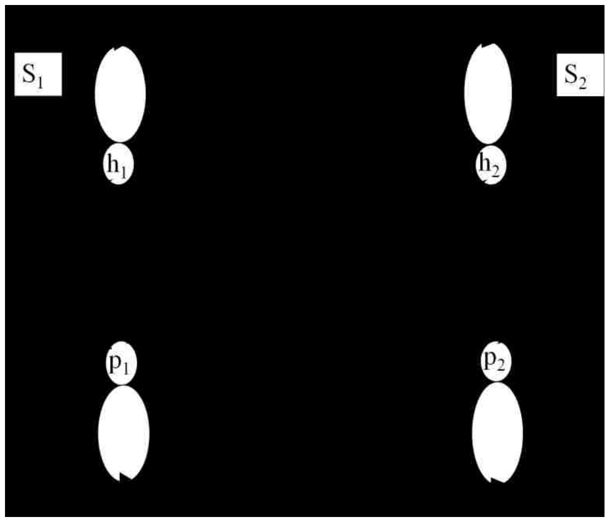
The structural aspects of this scenario can be obtained by linking the two subsystems. These two subsystems S_1 and S_2 are given through Equations 3.41 and 3.42 (Siljak, 1978), and are shown by dashed lines in Figure 3.11(a).

$$\begin{bmatrix} \dot{h_1} \\ \dot{p_1} \end{bmatrix} = \begin{bmatrix} \alpha_1 - \alpha_{11} h_1 & -\gamma_1 \\ \delta_1 p_1 & -\beta_1 - \theta_1 p_1 \end{bmatrix} \begin{bmatrix} h_1 \\ p_1 \end{bmatrix} \tag{3.41}$$

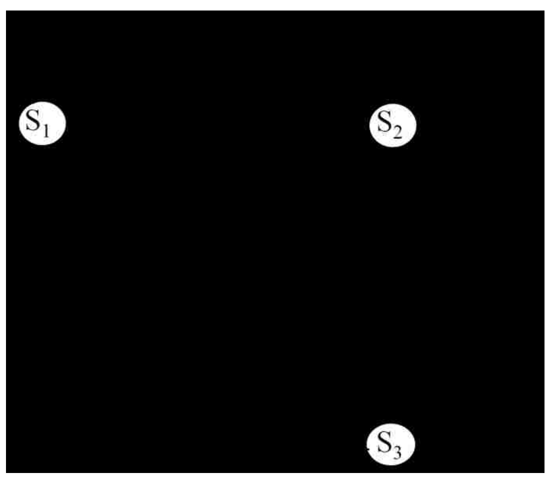
$$\begin{bmatrix} \dot{h_2} \\ \dot{p_2} \end{bmatrix} = \begin{bmatrix} \alpha_2 - \alpha_{22} h_2 & -\gamma_2 \\ \delta_2 p_2 & -\beta_2 - \theta_2 p_2 \end{bmatrix} \begin{bmatrix} h_2 \\ p_2 \end{bmatrix} \tag{3.42}$$

If we add another subsystem S_3, then the system is shown in Figure 3.11(b). The corresponding subsystem is represented in Equation 3.43.

$$\begin{bmatrix} \dot{h_3} \\ \dot{p_3} \end{bmatrix} = \begin{bmatrix} \alpha_3 - \alpha_{33} h_3 & -\gamma_3 \\ \delta_3 p_3 & -\beta_3 - \theta_3 p_3 \end{bmatrix} \begin{bmatrix} h_3 \\ p_3 \end{bmatrix} \tag{3.43}$$



(a)



(b)

Figure 3.11 Interconnected network analyses: (a) interconnected network digraphs and (b) a multi-city network.

In addition, Figure 3.11(b) shows the multi-city network and their interconnections ($\alpha_{12}, \alpha_{21}, \alpha_{32}, \alpha_{23}$) along with the structural characteristics. These individual cities have multiple subsystems that interact within themselves. In addition, these cities also are affected by the interactions between them. For example, the interactions can be among a freight corridor for transportation purposes or activities for the economic development. For a generalized framework, the interactions between these subsystems are represented through an interconnection matrix $\bar{E}$, and each of the individual elements is defined as shown in Equation 3.44.

$$\bar{e}_{ij} = \begin{cases} 1, & S_j\ can\ act\ on\ S_i \\ 0, & i = j\ or\ S_j\ cannot\ act\ on\ S_i \end{cases} \tag{3.44}$$

In other words, $\bar{e}_{ij} = 1$ if there is a dependency between $h_j\ and\ h_i$ from subsystem S_j to the subsystem S_i, and $\bar{e}_{ij} = 0$ if there is no line $h_j h_i$. To perform the analysis for the multi-city network in Figure 3.8(b), the corresponding interconnection matrix is given by Equation 3.45.

$$\bar{E} = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} \tag{3.45}$$

Furthermore, Equations 3.46 to 3.48 represent the dynamics of this network with the help of above interconnection matrix.

$$\begin{bmatrix} \dot{h_1} \\ \dot{p_1} \end{bmatrix} = \begin{bmatrix} \alpha_1 - \alpha_{11}h_1 & -\gamma_1 \\ \delta_1 p_1 & -\beta_1 - \theta_1 p_1 \end{bmatrix} \begin{bmatrix} h_1 \\ p_1 \end{bmatrix} + \begin{bmatrix} -\alpha_{12} & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} h_2 \\ p_2 \end{bmatrix} \tag{3.46}$$

$$\begin{bmatrix} \dot{h_2} \\ \dot{p_2} \end{bmatrix} = \begin{bmatrix} \alpha_2 - \alpha_{22}h_2 & -\gamma_2 \\ \delta_2 p_2 & -\beta_2 - \theta_2 p_2 \end{bmatrix} \begin{bmatrix} h_2 \\ p_2 \end{bmatrix} + \begin{bmatrix} -\alpha_{21} & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} h_1 \\ p_1 \end{bmatrix} + \begin{bmatrix} -\alpha_{23} & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} h_3 \\ p_3 \end{bmatrix} \tag{3.47}$$

$$\begin{bmatrix}\dot{h_3}\\ \dot{p_3}\end{bmatrix} = \begin{bmatrix}\alpha_3 - \alpha_{33}h_3 & -\gamma_3\\ \delta_3 p_3 & -\beta_3 - \theta_3 p_3\end{bmatrix}\begin{bmatrix}h_3\\ p_3\end{bmatrix} + \begin{bmatrix}-\alpha_{32} & 0\\ 0 & 0\end{bmatrix}\begin{bmatrix}h_2\\ p_2\end{bmatrix} \tag{3.48}$$

Similarly, this network can be extended to a more general network having *n* systems. Such a network can have multiple interconnections and interdependencies, and are represented by an interconnection matrix $\bar{E}$, as shown in Equation 3.49.

$$\bar{E} = \begin{bmatrix}\bar{e}_{11} & \cdots & \bar{e}_{1n}\\ \vdots & \ddots & \vdots\\ \bar{e}_{n1} & \cdots & \bar{e}_{nn}\end{bmatrix} \tag{3.49}$$

Also, the system vector for *n* systems, along with the coupling effect, is represented through Equations 3.50 and 3.51.

$$\dot{S} = AS + \mu\bar{E}S \tag{3.50}$$

$$\dot{S_\iota} = AS_i + \mu_{i1}\bar{e}_{i1}S_i + \mu_{i2}\bar{e}_{i2}S_2 + \mu_{i3}\,\bar{e}_{i3}S_3 + \cdots + \mu_{in}\bar{e}_{in}S_n \tag{3.51}$$

where:

S_i: system vector for ith system

μ_{ij}: The relationship parameter matrix for jth system

To summarize, the above equations can be utilized along with the proposed dynamical modeling approach to build models for individual cities. These models will help to understand the interconnections among multiple cities. The associated relationships among them are dependent on the nature and geographic characteristics, for example, waterways, freight corridors, and transportation hubs. This research provides a framework to increase the resolution and scope of study. In addition, it improves the model and enhances understanding of interconnected networks from the perspective of sustainable systems. Depending on the granularity, the effects from an individual city on the entire network can be studied.

3.6 Conclusions and Recommendations

The results suggest that the performance of TS and AS follows a periodic pattern with a phase lag. Also, there is a decreasing trend for the performance of ES. This trend makes the conditions unsustainable, and endangers the livability of future generations. This will result in the depletion of resources due to continuous improvements in the TS and AS. Therefore, it is necessary to understand the systems in unison and formulate appropriate policies that conserve resources without hindering growth, ultimately ensuring a healthy environment with the intention of providing a better and sustainable life for future generations.

The major contribution in this research is a novel approach to understand the dynamics of the three interdependent systems, using the concepts derived from classical predator-prey techniques. This system is highly non-linear in nature. Therefore, the capabilities of this modeling approach are restricted to understanding the theoretical and quantitative concepts within the SOS. The proposed modeling approach may provide useful information for researchers to modify and enhance such models for rigorous analysis of sustainable systems. As a result, this model can be used as a starting point to understand the behavior of SOS.

CHAPTER 4

DEVELOPMENT OF CONTROL MODELS FOR THE PLANNING OF SUSTAINABLE TRANSPORTATION SYSTEMS

4.1 Introduction

The theory of optimal control has been well developed for over forty years. With the advances of computer technique, optimal control is now widely used in multi-disciplinary applications such as biological systems, communication networks and socio-economic systems etc. (Wang, 2009). The applications of control systems in transportation systems have been extensively studied by multiple researchers. Strub and Bayen (2006) studied the optimal control of air traffic networks using continuous flow models. The authors used Eulerian models (control volume based) as compared to Lagrangian models (trajectory-based) and take into account all aircraft trajectories. Raschke et al. (2013) used a combinatorial optimization approach for group comparisons to minimize the cost of sample collection. Hooker et al. (1983) and Hooker (1988) studied the optimal control of automobiles to investigate the underlining principle of optimal driving with an objective of minimizing fuel consumption. However, in the early eighties, due to the limited availability of infrastructure, sensing technologies, and tools for traffic modeling and prediction, the study was unable to gain momentum in traffic management and in-vehicle systems.

Recent advances in the communication technology have led to emergence of new cooperative systems that utilize vehicle-to-vehicle (V2V) and/or vehicle-to-infrastructure (V2I) communication. These systems help improve safety, efficiency and reduce the environmental impacts of road traffic as compared to the existing ITS systems. The application of communication technology in ITS development has attracted broad attention with respect to vehicle ad-hoc network and V2V based ITS systems to improve road safety e.g. COOPERS (Farah et al., 2012). Nevertheless, few V2I systems have been developed to manage traffic fleets on road for energy and environmental purposes. As a result, there are increasing demand to develop intelligent infrastructure or roadside units that serve as a local management tool based on real life traffic conditions. Ma (2013) developed a methodological approach using optimal control theory to control the environmental impacts of live vehicle fleets. This study suggested that the technique is favorable for local V2I based traffic management applications. Furthermore, the technique can be extended for more complex optimal control problems in dynamic fleet management. Overall, the presence of cooperative system in ITS development makes it technically possible to implement dynamic guidance to drivers. In fact, this will benefit system efficiency, especially by means of fuel economy and environmental effects..

Lately, the applications of control systems have been visible in hybrid electric vehicles in deregulated electricity markets. The use of Plug-in hybrid electric vehicles (PHEVs) has been encouraged to primarily achieve two tasks: a) Reduce CO_2 emissions, and b) Diversify the fuel supply for the nation's transportation fleet. Rotering and Illic (2011) used PHEVs to reduce the transportation sector's dependency on oil. The authors argued that if their technique is implemented in a large scale environment without control, the peak load will increase significantly and the grid may be destabilized. The implemented algorithms were based on a forecast of future electricity prices and use dynamic programming to find the economically optimal solution for the vehicle owner. Kempton and Tomic (2005) examined the systems and process needed to store energy in vehicles and implement Vehicle-to-Grid power (V2G). The study discussed stabilizing the grid and supporting large-scale renewable energy systems. Sioshansi and Denholm (2009) studied the emissions impacts and benefits of PHEVs and V2G services. The authors inferred that by adding V2G power services, such as spinning reserves and energy storage, the emissions can be reduced drastically. Stephan and Sullivan (2008) studied the environmental and energy implications of PHEVs and suggested that CO_2 emissions will reduce by 25% in the short term and as much as 50% in the long term when compared to their conventional hybrid vehicles. The authors also discussed the CO_2 savings of replacing coal plants versus replacing conventional vehicles with PHEVs. Samras and Meisterling (2008) discussed the life cycle assessment of greenhouse gas emissions from PHEVs and its implications for policy analysis. They found out that PHEVs reduce GHG emissions by 32% compared to conventional vehicles, but have small reductions compared to traditional hybrids. Johnson et al. (2006) generated a MARKAL model of the U.S. that could be employed by federal and regional decision-makers to explore future scenarios of energy system development and the associated emissions. Miah et al. (2012) developed optimum policy for integration of renewable energy sources into power generation. The results demonstrated that control theory can be used successfully to formulate optimal socio-economic policies.

Researchers have formulated numerous models to incorporate sustainability through the use of various approaches. Nagurney and Nagurney (2010) developed a rigorous modelling and analytical framework for the design of sustainable supply chain networks. They provided both the network optimization modelling framework and an algorithm to compute solutions for design examples. Batagan (2011) emphasized the concept of smart solutions to achieve the sustainable development and identified the key elements of future smart cities. The model showed that economical sustainability and ecological sustainability are both individually necessary but insufficient conditions for sustainable development. The results highlighted that for a sustainable development, there is a need to reduce the non-renewable resources and to produce new resources using the smart solutions. Li and Lofgren (2000) analyzed the relationship of economic sustainability with natural resources. They characterized the long-run steady state, analyzed its asymptotic stability, and explored the transitional dynamics from any initial state. In addition, the conflict between present and future generations in a dynamic renewable resource model under a social welfare function was discussed.

Recently, researchers have focused their attention to incorporate sustainability into transportation systems by considering multiple systems simultaneously. Amekudki et al. (2009) presented a sustainability footprint framework and model useful to analyze the impacts of transportation and other infrastructure systems on regional sustainable development. In addition, the implications of this model for transport systems research, policy and practice were discussed. The contributions lie in introducing both spatial and temporal flexibility that may enable decision makers with widely different priorities to reach consensus on interim goals. Bohringer and Loschel (2006) investigated the use of computable general equilibrium (CGE) models for measuring the impacts of policy interference on economic, environmental, and social indicators. The authors found that operational CGE models used for energy–economy–environment (E3) analyses have a good coverage of central economic indicators. Paz et al. (2013) identified the performance measures within transportation, activity, and environmental system and later combined them to obtain performance indices using soft computing techniques. In addition, the authors provided key policy measures that affect the transportation, activity and environmental systems. Fiksel (2006) emphasized that a comprehensive systems approach is essential for effective decision making with respect to global sustainability, since industrial, social, and ecological systems are interlinked. The author suggested the use of dynamic modeling techniques, including biocomplexity, system dynamics, and thermodynamic analysis, to investigate the relationships between associated systems and policy making. They also provide recommendations to achieve progress in dynamic modeling and sustainable management of complex systems. Maheshwari et al. (2014) developed dynamical models using predator-prey techniques to understand the future trend of the performance indices over time. The study indicated that much research and simulations simulations still is needed to capture the behavior of such systems for application in policy making (Paz et al., 2014).

Although, the aforementioned researchers have done an excellent job by considering multiple systems and creating different sustainability models, there is a need to incorporate control in sustainability systems that can provide tools to decision makers for policy recommendations. As a result, the proposed research envisages incorporating sustainable considerations and providing solutions to stakeholders in policy making using control techniques. The scientific impact of the proposed research will be through the formulation of techniques, methods, and models that will help understand the relationships between public policy, and sustainability. The academic merit will be the application of optimal control theory methods in the design of public policy instruments.

This chapter is organized as follows. The data used in this research is presented in Section 4.2. Section 4.3 presents the mathematical model based on Lotka–Volterra prey–predator system leading to the problem formulation. Section 4.4 discusses the methodology used in this research. Numerical results are provided in Section 4.5. Section 4.6 presents the conclusions and recommendations.

4.2 Data

The data for the current research is obtained from the continental United States. The major data set comprises of the yearly performance measures ranging from 1990-2012, 23 years in total (Paz et al., 2013). Three major systems are defined in this research: Transportation System (TS), Activity System (AS), and Environmental System (ES). The TS includes the following performance measures: VMT/lane mile, Personal Spending on Transportation, and Transportation Service Index (TSI). The AS includes the following performance measures: GDP/capita, Education Index, and Life Expectancy. The ES includes the following performance measures: Air Pollution, Water Pollution, Energy Consumption, and Carbon-Dioxide Emissions. The data is obtained from various sources and organizations such as The World Bank, the United Nations, the Bureau of Transportation Statistics, and the U.S. Environmental Protection Agency. The multiple performance measures are combined using fuzzy logic to obtain the corresponding

Performance Indices (PIs). For example, performance measures such as VMT/lane mile, personal spending on transportation, and TSI are combined to obtain TSPI. Similarly, relevant performance measures are combined to obtain the ASPI and ESPI respectively. The PIs are calculated independently for each of the three systems. The following three steps are used to calculate the corresponding PI: (a) an inference step, (b) an aggregation step, and (c) a defuzzification step. The reliability of these PIs is verified using the existing trend for the corresponding performance measures. During the past two decades, these performance measures follow similar patterns with the periods of growth due to economic boom and downturn as a result of political uncertainties, recession, and financial crisis.

A comprehensive literature review was performed to choose the performance measures that take into account all the dimensions of Transportation, Economic, Environmental and Social systems relevant within the society. Based on the spatial and geographic characteristics of a particular location, the performance measures were selected. The framework to compute PIs was modular and flexible, and could accommodate more performance measures over time. Therefore, as the number of performance measures increases, the PIs will change; however, the overall trend of the all the PIs will remain comparable.

4.3 Mathematical Modeling

This section describes the variables and modeling equations used to define different systems of sustainability. The concept of predator-prey is relevant to biological systems in which two species interact. The predator–prey equation was developed independently by Lotka (1920) and Volterra (1931), and is often called the Lotka-Volterra model. These equations are a pair of first order, non-linear differential equations. In addition, they cannot be separated from each other and cannot be solved in closed form. The dynamic modeling equations defined in this research are the extension of Lotka-Volterra equations applicable to two species system (Miah et al., 2012) and three species system (Maheshwari et al., 2014). A modified version of Lotka-Volterra equations for three species system is presented in this research. The three variables that defines the state of a system are TS: x_1, the AS: x_2, and the ES: x_3. The corresponding modeling equations for the performance of TS, AS and ES can be represented by Equations 4.1 through 4.3 (Maheshwari et al., 2012; Maheshwari et al., 2014).

$$f_1 = \dot{x}_1 = \frac{dx_1}{dt} = a_{11}x_1(1 - b_1x_1) + a_{12}x_1x_2x_3(1 - b_1x_1), \tag{4.1}$$

$$f_2 = \dot{x}_2 = \frac{dx_2}{dt} = -a_{21}x_2(1 - b_2x_2) - a_{22}x_1x_2x_3(1 - b_2x_2) \tag{4.2}$$

$$f_3 = \dot{x}_3 = \frac{dx_3}{dt} = a_{31}x_1x_2x_3 + b_t\frac{dx_1}{dt} + b_a\frac{dx_2}{dt} \tag{4.3}$$

where $x_3 < 0$ and a_{11}, a_{12}, a_{21}, a_{22}, a_{31}, b_t, b_a, b_1 and b_2 are all parameters that need to be estimated. The parameters b_1 and b_2 are logistic growth parameters for TS and AS, respectively. The functions $f_1, f_2, and\ f_3$ denote the rate of change of TS, AS, and ES with respect to time.

4.3.1 Case Study

One example of a policy scenario takes into consideration investments in solar/energy-efficient technologies and their effects on TS, AS, and ES. Figure 4.1 explains this scenario through two layers. The first layer implies that an investment in emerging and green technologies will directly result in increase in economic activity and increase the employment. Additionally, the investment will result in better fuel efficiency for vehicles, ultimately decreasing fuel consumption.

The second layer looks at the indirect affects of the proposed policy. First, an increase in economic activity results in education standards and helps in increasing the life expectancy. Furthermore, it helps in managing urban sprawl and land-use changes, resulting in increased mobility and transportation. Second, a decrease in fuel consumption results in reduced pollution and greenhouse emissions. This is specially important to reduce the carbon footprint.

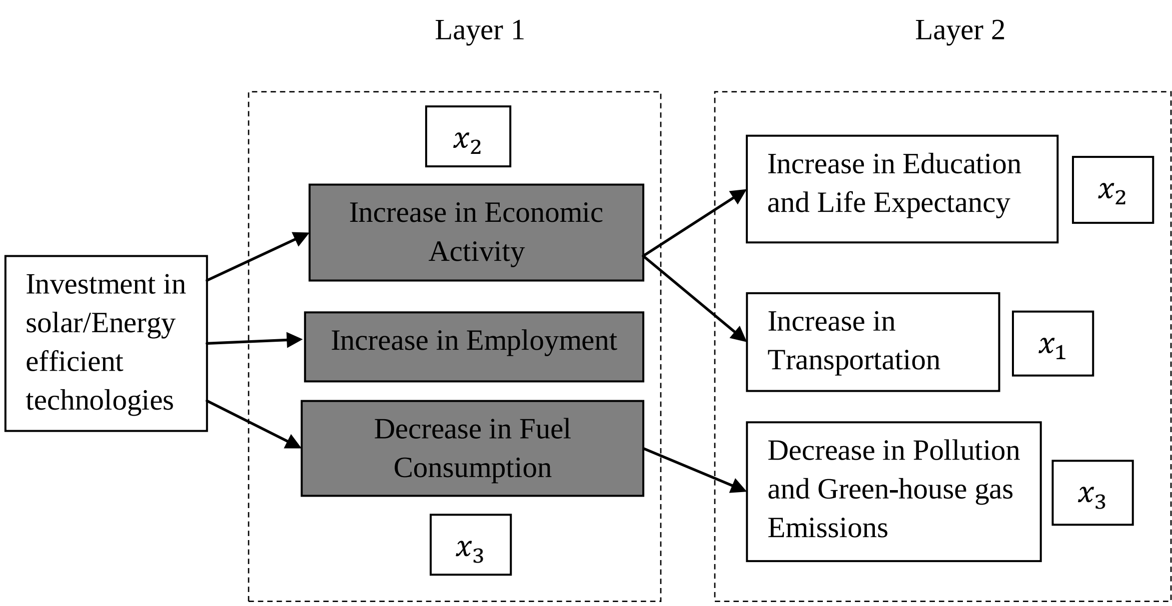


Figure 4.1 An Example of that effect that investment has on Transportation, Activity and Environmental Systems

4.3.2 Generalized Control Equations

This section discusses the generalized control equation and techniques to check the controllability of the system. The generalized form in vector format can be represented by Equations 4.4 through 4.7. The bold letters represent vectors.

$$\dot{\boldsymbol{x}} = f(\boldsymbol{x}) + g(\boldsymbol{x}).\boldsymbol{u}(t) \tag{4.4}$$

Where

$$f(\boldsymbol{x}) = \begin{bmatrix} f_1(x_1, x_2, x_3) \\ f_2(x_1, x_2, x_3) \\ f_3(x_1, x_2, x_3) \end{bmatrix} \tag{4.5}$$

$$g(\boldsymbol{x}) = \begin{bmatrix} g_{11}(x_1, x_2, x_3) & g_{12}(x_1, x_2, x_3) & g_{13}(x_1, x_2, x_3) \\ g_{21}(x_1, x_2, x_3) & g_{22}(x_1, x_2, x_3) & g_{23}(x_1, x_2, x_3) \\ g_{31}(x_1, x_2, x_3) & g_{32}(x_1, x_2, x_3) & g_{33}(x_1, x_2, x_3) \end{bmatrix} \tag{4.6}$$

$$\boldsymbol{u}(t) = \begin{bmatrix} u_1(t) \\ u_2(t) \\ u_3(t) \end{bmatrix} \tag{4.7}$$

Here, g_{ij}denotes the policy parameters and $\boldsymbol{u}$ is the control vector. However, for this particular policy scenario, Equation 4.4 can be represented by Equation 4.8.

$$\begin{bmatrix} \dot{x_1} \\ \dot{x_2} \\ \dot{x_3} \end{bmatrix} = f(\boldsymbol{x}) + \begin{bmatrix} 0 \\ g_{21}x_1 \\ 0 \end{bmatrix} u_1 + \begin{bmatrix} 0 \\ g_{22}x_2 \\ 0 \end{bmatrix} u_2 + \begin{bmatrix} 0 \\ 0 \\ g_{33}x_3 \end{bmatrix} u_3 \tag{4.8}$$

where parameters g_{21}, g_{22}, and g_{33} are associated with increase in transportation, increase in life expectancy, and decrease in greenhouse gases respectively.

4.3.3 Controllability for Non-Linear Systems

For any system, control techniques are applicable only if the system is controllable. Controllability for non-linear systems usually is defined with Lie Brackets. A nonlinear control system can be considered as a group of dynamical systems (vector fields) parameterized by a parameter called the ‘control’. It is expected that basic properties of such a system depend on interconnections between the different dynamical systems corresponding to different controls (Jakubczyk, 2001).

The dynamical systems presented in this research are represented by vector fields as this allows us to perform algebraic operations on them. An example of such an operation includes linear combinations and a product called Lie bracket, which is the basic tool that enables understanding the interactions between different vector fields. Let’s consider two vector fields $f(x)$ and $g(x)$ in R^n. Then the Lie bracket operation generates a new vector field, as defined by Equation 4.9.

$$[f, g] = \frac{\partial g}{\partial x} f - \frac{\partial f}{\partial x} g \tag{4.9}$$

In addition, higher-order Lie brackets can be defined by Equation 4.10 through 4.12.

$$\left(ad_f^1, g\right) = [f, g] \tag{4.10}$$

$$\left(ad_f^2, g\right) = [f, [f, g]] \tag{4.11}$$

....

$$\left(ad_f^k, g\right) = \left[f, \left(ad_f^{k-1}, g\right)\right] \tag{4.12}$$

Note: the “ad” is read as “adjoint”. For the system defined by Equation 4.13,

$$\dot{\boldsymbol{x}} = f(\boldsymbol{x}) + \textstyle\sum_{i=1}^{m} g_i(x)\, u_i \quad \text{where } m \text{ is the dimension of control vector.} \tag{4.13}$$

The generalized controllability matrix (C) can be written through Equation 4.14 as follows.

$$C = \left[g_1, g_2, \ldots g_m, \left[g_i, g_j\right], \ldots. \left[ad_{g_i}^k, g_j\right] \ldots\ldots [f, g_i], \ldots. \left[ad_f^k, g_i\right] \ldots\ldots\right] \tag{4.14}$$

where $g_1 = \begin{bmatrix} 0 \\ g_{21}x_1 \\ 0 \end{bmatrix}$, $g_2 = \begin{bmatrix} 0 \\ g_{22}x_2 \\ 0 \end{bmatrix}$, $g_3 = \begin{bmatrix} 0 \\ 0 \\ g_{33}x_3 \end{bmatrix}$

The Lie bracket of one of the elements in the controllability matrix is shown in Equation 4.15.

$$[f, g_1] = \frac{\partial g_1}{\partial x} f - \frac{\partial f}{\partial x} g_1 \tag{4.15}$$

where

$f(\boldsymbol{x}) = \begin{bmatrix} f_1(x_1, x_2, x_3) \\ f_2(x_1, x_2, x_3) \\ f_3(x_1, x_2, x_3) \end{bmatrix}$ defined through Equation 4.5.

Substituting $f(\boldsymbol{x})$ and g_1 into Equation 4.15 yields Equation 4.16.

$$[f, g_1] = \begin{bmatrix} 0 & 0 & 0 \\ g_{21} & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} f_1 \\ f_2 \\ f_3 \end{bmatrix} - \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} & \frac{\partial f_1}{\partial x_3} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} & \frac{\partial f_2}{\partial x_3} \\ \frac{\partial f_3}{\partial x_1} & \frac{\partial f_3}{\partial x_2} & \frac{\partial f_3}{\partial x_3} \end{bmatrix} \begin{bmatrix} 0 \\ g_{21}x_1 \\ 0 \end{bmatrix} \tag{4.16}$$

Solving Equation 4.16 by matrix multiplication results in Equation 4.17.

$$[f, g_1] = \begin{bmatrix} 0 \\ g_{21}f_1 \\ 0 \end{bmatrix} - \begin{bmatrix} (\frac{\partial f_1}{\partial x_2}) g_{21}x_1 \\ (\frac{\partial f_2}{\partial x_2}) g_{21}x_1 \\ (\frac{\partial f_3}{\partial x_2}) g_{21}x_1 \end{bmatrix} \tag{4.17}$$

Later, performing the arithmetic calculations on Equation 4.17 results in Equation 4.18.

$$[f, g_1] = \begin{bmatrix} -(\frac{\partial f_1}{\partial x_2}) g_{21}x_1 \\ (g_{21}x_1) - (\frac{\partial f_2}{\partial x_2}) g_{21}x_1 \\ -(\frac{\partial f_3}{\partial x_2}) g_{21}x_1 \end{bmatrix} \tag{4.18}$$

The C matrix including some elements can be written as shown in Equation 4.19.

$$C = [g_1, g_3, [f, g_1]] \tag{4.19}$$

Substituting the values of g_1, g_3, and $[f, g_1]$ into Equation 4.19 results in Equation 4.20.

$$C = \begin{bmatrix} 0 & 0 & -(\frac{\partial f_1}{\partial x_2})g_{21}x_1 \\ g_{21}x_1 & 0 & (g_{21}x_1) - (\frac{\partial f_2}{\partial x_2})g_{21}x_1 \\ 0 & g_{33}x_3 & -(\frac{\partial f_3}{\partial x_2})g_{21}x_1 \end{bmatrix} \tag{4.20}$$

The determinant of Equation 4.20 is calculated, and the criterion is to prove that Equation 4.21 holds true for C to be of Rank 3.

$$\left(\frac{\partial f_1}{\partial x_2}\right)(g_{21}x_1)^2 g_{33}x_3 \neq 0 \tag{4.21}$$

Previously from Equation 4.1, it is known that

$$f_1 = \dot{x}_1 = \frac{dx_1}{dt} = a_{11}x_1(1 - b_1x_1) + a_{12}x_1x_2x_3(1 - b_1x_1)$$

Substituting f_1 in Equation 4.21 yields Equation 4.22.

$$\frac{\partial f_1}{\partial x_2} = a_{12}x_1x_3(1 - b_1x_1) \neq 0 \; for \; x_1 \neq \frac{1}{b_1} \tag{4.22}$$

As a result, C has Rank 3 everywhere; hence, the system is controllable.

4.4 Methodology

This section discusses the methodology and the numerical algorithm used in this research. The objective was to minimize the cost function such that the investments were minimized. The solution of the problem could be found using The Hamilton-Jacobi-Bellman Equation (Kirk, 2004). The current process is described by the state equation, and the problem is to find an admissible control $\boldsymbol{u}^*$ that causes the system in Equation 4.23.

$$\dot{\boldsymbol{x}}(t) = \boldsymbol{a}(\boldsymbol{x}(t), \boldsymbol{u}(t), t) \tag{4.23}$$

to follow an admissible trajectory $\boldsymbol{x}^*$ that minimizes the performance measure, as shown in Equation 4.24. To design the control law, Equation 4.24 is defined as

$$\boldsymbol{J}(\boldsymbol{u}) = h\big(\boldsymbol{x}(t_f), t_f\big) + \int_{t_o}^{t_f} g(\boldsymbol{x}(t), \boldsymbol{u}(t), t)dt \tag{4.24}$$

where h and g are specified functions, t_o and t_f are fixed, and t is a dummy variable of integration.

Assume the cost function g takes the following form in Equation 4.25. The objective is to minimize the cost function in Equation 4.25 to attain the desired state.

$$g(\boldsymbol{x}(t), \boldsymbol{u}(t), t) = (x_1 - x_{f1})^2 + (x_2 - x_{f2})^2 + (x_3 - x_{f3})^2 + u_1^2 + u_2^2 + u_3^2 \tag{4.25}$$

subject to the constraints: $u_1 > 0$, $u_2 > 0$, and $u_3 > 0$.

Let $e_1 = (x_1 - x_{f1})$, $e_2 = (x_2 - x_{f2})$, and $e_3 = (x_3 - x_{f3})$; where e_1, e_2, and e_3 represent the error with respect to values for the initial and final states; $x_f's$ are the desired (final) state of the system. Since investment always is positive, it cannot be taken out of the system. Therefore, it is assumed that u_1, u_2, and u_3, which represent investments, all are greater than zero. As a result, the cost function in Equation 4.25 becomes a constraint optimization problem.

Substituting the values for x_1, x_2, and x_3 in terms of e_1, e_2, and e_3 into Equations 4.1 through 4.3 changes to Equations 4.26 through 4.28.

$$f_1 = \dot{e}_1 = \frac{dx_1}{dt} = a_{11}(e_1 + x_{f1})\{1 - b_1(e_1 + x_{f1})\} + a_{12}(e_1 + x_{f1})(e_2 + x_{f2})(e_3 + x_{f3})\{1 - b_1(e_1 + x_{f1})\} \tag{4.26}$$

$$f_2 = \dot{e}_2 = \frac{dx_2}{dt} = -a_{21}(e_2 + x_{f2})\{1 - b_2(e_2 + x_{f2})\} - a_{22}(e_1 + x_{f1})(e_2 + x_{f2})(e_3 + x_{f3})\{1 - b_2(e_2 + x_{f2})\} \tag{4.27}$$

$$f_3 = \dot{e}_3 \ = \frac{dx_3}{dt} = a_{31}(e_1 + x_{f1})(e_2 + x_{f2})(e_3 + x_{f3}) + b_t \frac{dx_1}{dt} + b_a \frac{dx_2}{dt} \tag{4.28}$$

We define the Hamiltonian H with Equation 4.29.

$$H(\boldsymbol{e}(t), \boldsymbol{u}(t), \boldsymbol{p}(t), t) = g(\boldsymbol{e}(t), \boldsymbol{u}(t), t) + \boldsymbol{p}^{\boldsymbol{T}}(t)[\boldsymbol{a}(\boldsymbol{e}(t), \boldsymbol{u}(t), t)] \tag{4.29}$$

Substituting the values of g from Equation 4.25, and $\dot{\boldsymbol{x}}$ from Equation 4.8 into Equation 4.29 yields Equation 4.30.

$H =$

$e_1{}^2 + e_2{}^2 + e_3{}^2 + u_1^2 + u_2^2 + u_3^2 +$

$$[p_1 \quad p_2 \quad p_3]\begin{bmatrix} f_1(e) \\ f_2(e) + g_{21}(e_1 + x_{f1})u_1 + g_{22}(e_2 + x_{f2})u_2 \\ f_3(e) + g_{33}(e_3 + x_{f3})u_3 \end{bmatrix} \tag{4.30}$$

The generalized form after solving the matrices in Equation 4.30 is given by Equation 4.31.

$H = e_1{}^2 + e_2{}^2 + e_3{}^2 + u_1^2 + u_2^2 + u_3^2 + p_1 . f_1(e) + p_2 . \{f_2(e) + g_{21}(e_1 + x_{f1})u_1 +$

$g22e2+xf2u2+p3.f3e+g33e3+xf3u3$ (4.31)

In order to design the optimal control, the necessary conditions that must be satisfied are represented by Equations 4.32 through 4.35 (Kirk, 2004).

$$\dot{\boldsymbol{e}}^*(t) = \frac{\partial H}{\partial \boldsymbol{p}}(\boldsymbol{e}^*(t), \boldsymbol{u}^*(t), \boldsymbol{p}^*(t), t) \tag{4.32}$$

$$\dot{\boldsymbol{p}}^*(t) = -\frac{\partial H}{\partial \boldsymbol{e}}(\boldsymbol{e}^*(t), \boldsymbol{u}^*(t), \boldsymbol{p}^*(t), t) \tag{4.33}$$

$$\boldsymbol{0} = \frac{\partial H}{\partial \boldsymbol{u}}(\boldsymbol{e}^*(t), \boldsymbol{u}^*(t), \boldsymbol{p}^*(t), t) \tag{4.34}$$

$$\left[\frac{\partial h}{\partial \boldsymbol{e}}(\boldsymbol{e}^*(t_f), t_f) - \boldsymbol{p}^*(t_f)\right]^T \delta \boldsymbol{e}_f + \left[H(\boldsymbol{e}^*(t_f), \boldsymbol{u}^*(t_f), \boldsymbol{p}^*(t_f), t_f) + \frac{\partial h}{\partial t}(\boldsymbol{e}^*(t_f), t_f)\right] \delta t_f = 0 \tag{4.35}$$

Now, let us consider the boundary conditions specifically to the proposed policy scenario. It is assumed that the final time is fixed and the desired state is specified. Since $\boldsymbol{x}(t_f)$ and t_f are specified, $\delta \boldsymbol{e}_f = \boldsymbol{0}$ and $t_f = 0$, which satisfy Equation 4.35. To get the optimal control, the partial derivative of the Hamiltonian with respect to the control variable is taken and equated to zero, as shown in Equation 4.34. This can be converted to individual equations, as given by Equation 4.36.

$$\frac{\partial H}{\partial u_1} = 0, \frac{\partial H}{\partial u_2} = 0 \text{ and } \frac{\partial H}{\partial u_3} = 0 \tag{4.36}$$

Substituting the value of H from Equation 4.30 into Equation 4.36 results in Equation 4.37 through 4.39.

$$\frac{\partial H}{\partial u_1} = 2u_1 + p_2.g_{21}(e_1 + x_{f1}) \tag{4.37}$$

$$\frac{\partial H}{\partial u_2} = 2u_2 + p_2.g_{22}(e_2 + x_{f2}) \tag{4.38}$$

$$\frac{\partial H}{\partial u_3} = 2u_3 + p_3.g_{33}(e_3 + x_{f3}) \tag{4.39}$$

Equations 4.37 through 4.39 are all equated to zero, as a result, yields Equations 4.40 through 4.42, respectively.

$$u_1 = -\frac{p_2.g_{21}.(e_1+x_{f1})}{2} \tag{4.40}$$

$$u_2 = -\frac{p_2.g_{22}.(e_2+x_{f2})}{2} \tag{4.41}$$

$$u_3 = -\frac{p_3.g_{33}.(e_3+x_{f3})}{2} \tag{4.42}$$

As evident from Equations 4.40 through 4.42, control variables are dependent on many other variables. To solve them, Equation 4.31 and Equation 4.32 are utilized; the results are shown in in Equations 4.43 through 4.45.

$$\frac{\partial H}{\partial p_1} = f_1(e) = \dot{e}_1^* \tag{4.43}$$

$$\frac{\partial H}{\partial p_2} = f_2(e) + g_{21}\left(e_1 + x_{f1}\right)u_1 + g_{22}\left(e_2 + x_{f2}\right)u_2 = \dot{e}_2^* \tag{4.44}$$

$$\frac{\partial H}{\partial p_3} = f_3(e) + g_{33}\left(e_3 + x_{f3}\right)u_3 = \dot{e}_3^* \tag{4.45}$$

Additionally, Equation 4.31 and Equation 4.33 are combined to get Equations 4.46 through 4.48.

$-\frac{\partial H}{\partial e_1} = 2e_1 + p_1.\left\{1 - 2b_1\left(e_1 + x_{f1}\right)\right\}.\left\{a_{11} + a_{12}\left(e_2 + x_{f2}\right)\left(e_3 + x_{f3}\right)\right\} -$

$p_2.a_{22}\left(e_2 + x_{f2}\right)\left(e_3 + x_{f3}\right).\left\{1 - b_2\left(e_2 + x_{f2}\right)\right\} + p_2.g_{21}u_1 + p_3.\left[a_{31}\left(e_2 + x_{f2}\right)\left(e_3 +\right.\right.$

$xf3+bt.1-2b1e1+xf1.a11+a12e2+xf2e3+xf3-baa22e2+xf2e3+xf3.1-b2e2+$

$xf2=p1*$ (4.46)

$-\frac{\partial H}{\partial e_2} = 2e_2 + p_1.a_{12}\left(e_1 + x_{f1}\right)\left(e_3 + x_{f3}\right)\left\{1 - b_1\left(e_1 + x_{f1}\right)\right\} - p_2.\left\{1 - 2b_2\left(e_2 +\right.\right.$

$xf2.a21+a22e1+xf1e3+xf3+p2.g22u2+p3.a31e1+xf1e3+xf3+bta12e1+xf1e$

$3+xf3.1-b1e1+xf1-ba1-2b2e2+xf2.a21+a22e1+xf1e3+xf3=p2*$

(4.47)

$-\frac{\partial H}{\partial e_3} = 2e_3 + p_1.a_{12}\left(e_1 + x_{f1}\right)\left(e_2 + x_{f2}\right).\left\{1 - b_1\left(e_1 + x_{f1}\right)\right\} - p_2.a_{22}\left(e_1 +\right.$

$xf1e2+xf2.1-b2e2+xf2+p3.a31e1+xf1e2+xf2+bta12e1+xf1e2+xf2.1-b1e1$

$+xf1-baa22e1+xf1e2+xf2.1-b2e2+xf2+p3.g33u3=p3*$

(4.48)

To solve the system of equations defined by Equations 4.40 through 4.48, numerical techniques are used. One such algorithm is explained in Section 4.4.1.

4.4.1 Numerical Algorithm

The above system of Equations can be solved using steepest descent method to find optimal controls and trajectories. This basic algorithm is based on gradient technique (Moss and Kwoka, 2010) which is implemented on MATLAB (Wang, 2009). The key steps of the proposed algorithm are described below.

Step 1 Subdivide the interval $[t_0, t_f]$ into N equal subintervals and assume a piecewise-constant control $u^{(0)}(t) = u^{(0)}(t_k)$, $t \in [t_k, t_{k+1}]$, $k = 0,1,2, \dots. N-1$

Step 2 Apply the assumed control $u^{(i)}$ to integrate the state equations from t_0 to t_f with initial conditions $e(t_0) = e_0$ and store the state trajectory $e^{(i)}$.

Step 3 Apply $u^{(i)}$ and $e^{(i)}$ to integrate costate equations backward, i.e., from $[t_f, t_0]$. The “initial value" $p^{(i)}(t_f)$ can be obtained by Equation 4.49.

$$p^{(i)}(t_f) = \frac{\partial h}{\partial e}(p^{(i)}(t_f)) \tag{4.49}$$

Evaluate $\frac{\partial H^{(i)}(t)}{\partial u}, t \in [t_0, t_f]$ and store this vector.

Step 4 If

$$\left\|\frac{\partial H^{(i)}}{\partial u}\right\| \leq \gamma \quad \text{and} \tag{4.50}$$

$$\left\|\frac{\partial H^{(i)}}{\partial u}\right\|^2 = \int_{t_0}^{t_f} \left[\left\|\frac{\partial H^{(i)}}{\partial u}\right\|\right]^T \left[\left\|\frac{\partial H^{(i)}}{\partial u}\right\|\right] dt \tag{4.51}$$

then stop the iterative procedure. Here γ is a preselected small positive constant used as a tolerance.

If Equation 4.50 is not satisfied, adjust the piecewise-constant control function by using Equation 4.52.

$$u^{(i+1)}(t_k) = u^{(i)}(t_k) - \tau \frac{\partial H^{(i)}}{\partial u}(t_k),\ k = 0,1,2, \dots . N - 1 \tag{4.52}$$

Replace $u^{(i)}$ by $u^{(i+1)}$and return to step 2. Here, τ is the step size.

The parameters values; g_{21}, g_{22}, and g_{33}, are obtained based on the following information. For calculating g_{21}, results are used from the econometric model by Pozdena (2009). The study found that VMT is a major driver of GDP in the short run rather than the long run. Subsequently, research indicated that a 1% change in VMT per capita resulted in a 0.9% change in GDP per capita within two years, and a 0.46% change in 20 years.

For calculating g_{22}, a regression model was studied based on the relationship between life expectancy and GDP per capita (Statistical Consultants Ltd, 2010). The study highlighted functions that increase at a decreasing rate, including multiplicative (hyperbolas) and logarithmic functions. The regression output, shown in Equation 4.53, was estimated based on data for countries with life expectancy of at least 40.

$$y = 75.49 - \frac{48{,}270}{x+1{,}200} + 0.0001401x \tag{4.53}$$

where y is the life expectancy at birth, and x is GDP per capita (PPP). The model fits quite well to the data, with the R^2 value equal to 75.9%. This represents a fairly good model for estimating purposes.

The details for calculating g_{33} are discussed below. Research shows that today, hybrid gas-electric engines can cut global warming pollution by one-third or greater. If automakers use the existing technology to raise fuel-economy standards for new cars and light trucks to a combined 40 mpg, CO_2 pollution ultimately would drop by more than 650 million tons per year (Natural Resources Defense Council, 2005). According to

Morrow et al. (2010), transportation taxes, the most effective policy, could reduce the annual U.S. GHG emissions to only 7% below 2005 levels by the year 2020. The study emphasized that none of the existing policy scenarios – a CO_2 tax, an extended Corporate Average Fuel Economy program (CAFÉ) of the National Highway Traffic Safety Administration, a tax credit, a fuels tax, or a combination of these methods – can stop annual GHG emissions from continuing to increase beyond the year 2025. The primary reason is due to the faster growth in population and income per capita than in GHG emissions reduction. The new standards for fuel economy of conventional vehicles (passenger cars) is expected to increase from 30 mpg to 40 mpg from 2010 to 2030. During that same period, the GHG emissions are expected to decrease by more than 10%, based on the most effective policy (Morrow et al., 2010).

4.5 Results and Analysis

We computed the investment profile over time, which optimizes the given objective function. An increasing demand worldwide for investment in fuel-efficient technologies was taken into account in the objective cost function. The idea was to minimize the error, representing the difference between the values for the initial state and the final state such that the desired levels of respective states – TS, AS, and ES – could be attained and maintained. The case illustrated in this research was for fixed time.

Figure 4.2 shows the evolution of error over time, with red, green, and blue curves showing the trends for error in TS, AS, and ES, respectively. The *x* axis represents the years starting from year 1990 till 2050, and the *y*-axis represents the error. It is evident that for 60-year period, such control functions were defined that enable the system to approach towards its desired state. In particular, TS and AS were able to attain the desired states. In the current context, which was treated as a closed system, it was observed that any investment in ES would not contribute towards its improvement. However, the control designed in this research limited the degradation of ES by placing appropriate controls on TS and AS.

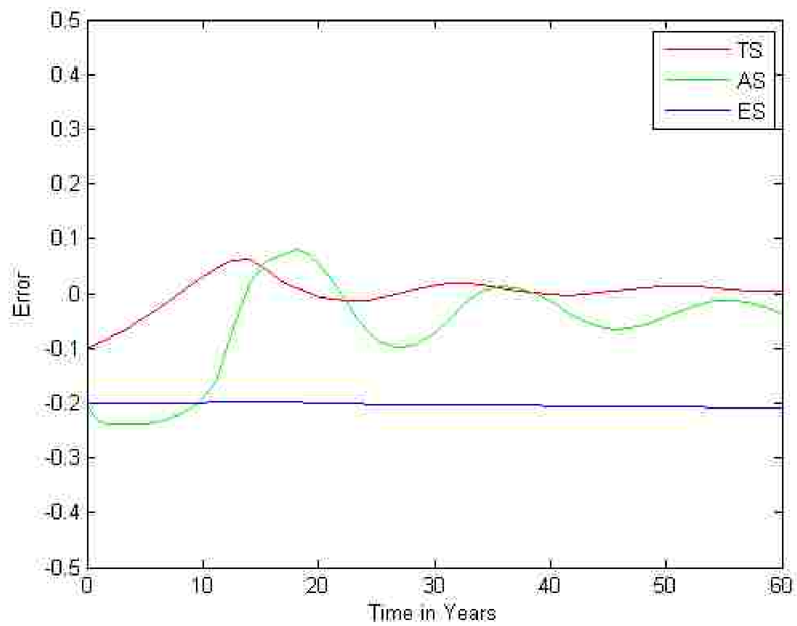


Figure 4.2 Evolution of error over time

Figure 4.3 shows the evolution of control over time in the last iteration. The *x* axis represents time in years whereas *y* axis displays the value of the control variable. The red, green, and blue curves represent the control profiles for u_1, u_2, and u_3, representing TS, AS, and ES, respectively. The initial control profiles are given by Equations 4.54 through 4.56 and the final control profiles are shown in Figure 4.3.

$$u_1 = 0.90 * \sin\left(\frac{n\pi}{t_f}\right) + 0.90 \tag{4.54}$$

$$u_2 = 0.90 * \sin\left(\frac{n\pi}{t_f}\right) + 1.0 \tag{4.55}$$

$$u_3 = 0 \tag{4.56}$$

where $n = 1, 2 \ldots .60$, and $t_f = 60$.

As evident from Figure 4.3, substantial investments were made initially to jump start the economy; later, the amount of investment decreased over time. However, at certain time in the future, the AS had to be replenished with investments to sustain the economic balance.

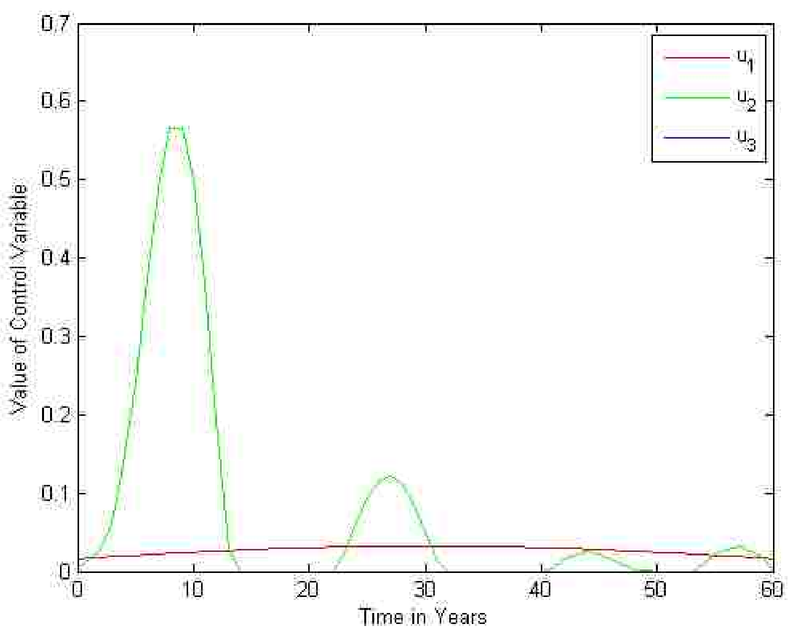


Figure 4.3 Evolution of control over time

The value of the performance measure as a function of iteration number is shown in Figure 4.4. The *x* axis represents the iteration number, and the *y* axis denotes the cost. The system is highly non-linear in nature; hence, getting a reasonable solution for such a system was extremely difficult. However, a convergence towards the solution was achieved as the number of iteration increased. It was evident that the system was able to converge, and the cost function was minimized for these conditions.

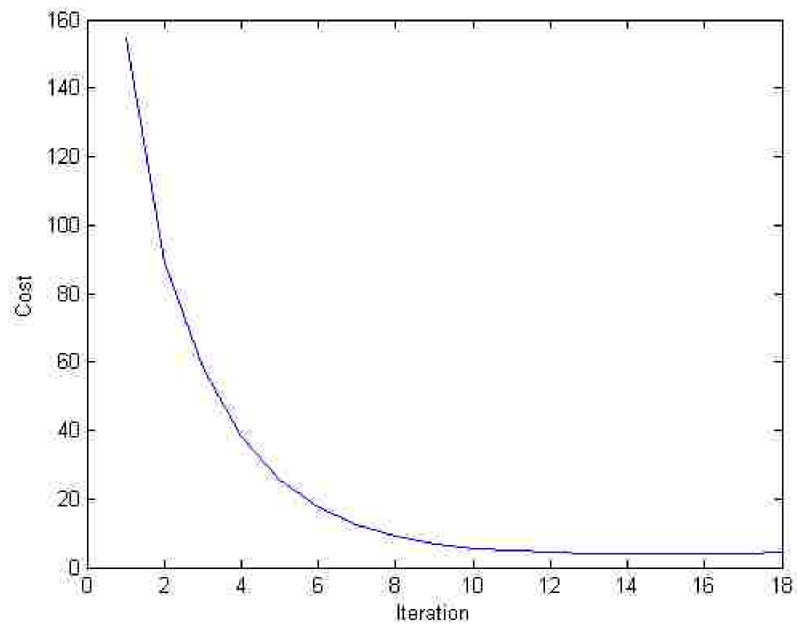


Figure 4.4 Cost over iterations

4.6 Conclusions and Recommendations

This research focused on the use of optimal control theory for policy design in the context of sustainability. To achieve this, a macroscopic system was analyzed consisting of three states: transportation, activity, and environment systems. Later, a dynamic model for the planning and development of sustainable transportation systems was developed, given by three nonlinear differential equations representing the dynamics of the three independent states. A policy scenario regarding investment in energy-efficient technologies and their effects on the states was developed to make investment decisions. The technique presented in this research was modular; therefore, multiple simulations, iterations, and runs could be performed, depending on the values of the desired states and the time period under study. Optimal control techniques were used to design the controls with the desired final state and time.

The results demonstrated that it is possible to formulate an optimal control to achieve the desired target. The numerical results were based on actual parameters, and provided the long-term trends of the states. This methodology will be helpful to policy makers in developing optimal decisions. The contribution of this research work was the introduction of a systems and controls methodology for developing optimal policies in the design of sustainable systems. A novel approach was developed by means of macro-level modeling that could be translated into decision making at the micro-level.

Moreover, to understand the control dynamics of components of individual sub-systems, or to study microscopic systems, such tools as System Dynamics and NetLogo have been widely used in prior research. These tools are classic examples in multi-agent modeling. The importance of such multi-agent models has attracted researchers and institutions from all over the world. In addition, research focusing specifically on their applications has gained significant attention in recent years. These models are widely used in many fields, including epidemiology, biology, life sciences, social sciences, networks, humanities, and engineering.

One of the potential recommendations of this research is to delve deeper into the dynamics of the individual sub-systems and understand their effects on decision making. This can enhance understanding of such systems from a micro-level perspective and provide future direction to design optimal policies.

CHAPTER 5

DEVELOPMENT OF A FRAMEWORK TO EVALUATE PROJECTS USING DYNAMIC TRAFFIC ASSIGNMENT MODELS

5.1 Introduction

The identification and selection of performance measures plays an important role in any decision making process. This helps the policy makers to allocate appropriate resources for prospective future improvements and evaluate projects. A myriad of literature is available that captures multiple performance measures within the Transportation, Activity and Environmental systems (Litman, 2007; Jeon et al., 2010; Zheng et al., 2011; Zietsman et al., 2006; Harger & Mayer, 1996; Yedla & Shrestha, 2003; Paz et al., 2013; Awasthi et al., 2011). These systems are interdependent and changes in one system directly affect the other. For example, continuous increase in vehicular traffic as a result of economic development results in increased fuel consumption, and that ultimately leads to increased CO_2 emissions and air pollutants. These emissions have a huge impact on the human health, environment and the society, and are difficult to estimate in monetary terms. Some of the performance measures that can be estimated include crashes, emissions (greenhouse gases and air pollutants), fuel consumption, vehicle operating costs, travel time reliability, etc. The following literature presents state of the art models, techniques and applications used by researchers to estimate performance measures for transportation corridors/networks and applied in different scenarios and alternatives.

There are primarily two type of models to assess effects on traffic safety; accident-risk–based models (ARBM), and accident prediction models (APM). ARBMs are descriptive models based on traffic accident and exposure data whereas APMs are based on available data to quantify the relationship between accidents and traffic characteristics (speed or flow). The ARBM assumes that the individual probability of being involved in a crash increases linearly with exposure. Lord (2002) described the non-linear relationship between crashes and exposure. As a result, safety research primarily focused on APM (Sawalha & Sayed, 2005; Lord, 2001). Basic APM used power function of the flow with geometric parameters for links (Greibe, 2003; Lord et al., 2005; Reurings et al., 2006) as well as intersections (Maycock & Hall, 1984; Lord & Persaud, 2004; Rencelj, 2009). In addition, some models are based on traffic characteristics such as hourly volumes, speeds, densities and volume-capacity (v/c) ratios (Garber & Gadiraju, 1989; Martin, 2002; Hiselius, 2004; Lord et al., 2005).

Researchers have used simulation models or travel demand models (TDM) to estimate emissions and fuel consumption. There are basically two types of emission models – average- speed based and instantaneous-speed based. Ahn et al. (2002) illustrated the development of microscopic energy and emission models for eight light duty vehicles using nonlinear multiple regression and neural network techniques. The study indicated that fuel consumption and emissions are more sensitive to the level of vehicle acceleration as compared to the vehicle speed. Rakha et al. (2004) and Ahn and Rakha (2003) used instantaneous speed and acceleration based emissions model VT-micro and combined with DTA model INTEGRATION to estimate emissions. Coelho et al. (2006) formulated three instantaneous speed based functions to estimate emissions and integrated them with aaSIDTA traffic model for roundabout analysis. Fomunung et al. (1999) developed an ordinary least-squares regression model to calculate NO_x emissions of light duty vehicles for the Atlanta, GA metropolitan region. Cappiello (2002) formulated an average speed-based emission model based on a probabilistic approach to calculate the acceleration and deceleration. Bottom (2000) used the microscopic traffic simulation model to estimate the CO_2 emissions under different strategies of route guidance. Mensink and Cosemans (2008) used the output from microscopic model PARAMICS to estimate emissions based on speed and acceleration. In addition, Servin et al. (2006) integrated PARAMICS with a load-based emission model CMEM to evaluate the impact of intelligent speed adaptation on energy and emissions. Kun and Lei (2007) integrated VISSIM with CMEM to estimate traffic emissions for evaluation of traffic control strategies. Huang et al. (2009) used VISSIM in conjunction with QUARTET (average-speed based) and MODEM (instantaneous-speed based) emission model to perform a comparative study during road maintenance works. MOTC, Taiwan (2010) computed the fuel consumption and emission factor and used VISSIM to estimate CO_2 emissions. Ambrosino et al. (1999) integrated the traffic assignment model EMME2 and AIMSUN2 by using integrated data base (IDB) and analyzed the impact of traffic strategies in the reduction in fuel consumption and emissions.

Furthermore, Sydow et al. (1997) used traffic simulation model DYNEMO and integrated with fuel consumption and emission database DYMOS for estimation of greenhouse gas emissions. Gran (1996) used data from Norwegian Institute for Air

Research to calculate the CO and NO_x emissions for Oslo region in Norway. Anderson et al. (1996) used Integrated Model of Urban Land-Use and Transportation for Environment Analysis to estimate the average speed and volume of each link. Later, the vehicular emissions were obtained by the integration of above model with MOBILE5. Paz et al. (2011) analyzed a dynamic traffic assignment (DTA) model DynusT, and the average-speed based emission model EMFAC to estimate emissions and fuel consumption for truck alternatives in the Las Vegas region. Their study was robust and was based on average hourly volume on any link in the network. However, using average hourly volumes may lead to slightly misleading calculations. Bai et al. (2007) used the mesoscopic DTA model Dynasmart-P and EMFAC to estimate emissions for trip based as well as link based traffic data. Lin et al. (2011) integrated DTA models with MOVES (Motor Vehicle Emission Simulator) for project level emissions analysis.

Considering the level of resolution used to model network traffic flows, modeling approaches can be categorized as macroscopic, microscopic, or mesoscopic. Normally, macroscopic approaches involve static traffic assignment models that enable the estimation of flow patterns on a regional scale but without any temporal resolution. These types of models use macroscopic traffic flow relationships to determine link travel times based on link flows. The TDM aggregates the origin-destination (OD) matrices across all modes before the traffic assignment step. As a result, the model cannot differentiate between truck and car assignments. Hence, the existing TDM cannot be directly used to conduct the desired analysis. In addition, the implementation of a multiclass assignment using a TDM framework requires addressing algorithmic and computational issues.

Multiclass models are computationally intensive and increase the complexity as compared to single class models. The travel cost functions in single class are symmetric and separable, hence convex optimization techniques can be used to find the solution; whereas in multiclass models, the travel cost functions are non-symmetric and non-separable, hence convex optimization techniques are not applicable (Patriksson, 2003). In addition, TDM models cannot capture key dynamic characteristics such as congestion propagation (e.g., spillback/spillover).

In contrast, microscopic models enable the explicit modeling of individual vehicles as well as temporal variations in traffic flow in the order of 0.1 to 1.0 seconds. In addition, they illustrate detailed traffic characteristics, such as lane changing behavior, acceleration/deceleration, and queuing related phenomena like spillback/spillover. However, this type of modeling requires a substantial amount of computational time and data collection efforts. As a result, it is very difficult and expensive to develop them for large-scale systems.

To overcome some of these limitations, many emerging planning strategies such as congestion pricing and the operational deployment of information provision services require modeling approaches that enable a greater level of detail than macroscopic models and with a much larger geographical scope than microscopic models. Mesoscopic models combine micro and macro level capabilities and incorporate many time-dependent traffic flow characteristics, such as spillback/spillover on a regional-level scale, for instance, a large urban transportation network with thousands of links, nodes, ODs, and vehicles. Thus, mesoscopic models combine many macroscopic and microscopic modeling capabilities.

Considering the broad impact of the alternatives under evaluation and the need to model and reroute individual vehicles, this study developed a mesoscopic and simulation-based DTA model based on the existing regional TDM. The TDM for the Las Vegas Roadway Network was provided by the Regional Transportation Commission of Southern Nevada. Most of the existing DTA models load individual vehicles into the network and solve a traffic assignment problem considering the operational characteristics of vehicles. This study requires a DTA capability that considers multiples classes of vehicles in terms of their routing strategies and behavior including trucks and regular passenger cars.

There are differences in calculating performance measures using static vs dynamic approaches. Kockelman et al. (2012) developed a framework in her "Project Evaluation Toolkit" for estimating many performance metrics, but using a static modeling approach. Paz et al. (2011) used DTA model DynusT to compute multiple performance measures and perform a benefit-cost analysis for truck alternatives in Las Vegas region. Maheshwari & Paz (2015) developed a methodology to evaluate projects using DTA models. The DTA model provides the capability to estimate traffic characteristics in an accurate manner as compared to static approaches. As a result, this research proposes a DTA simulation model to estimate the relevant performance measures (travel time, crashes, emissions, fuel consumption and vehicle operating costs) for Las Vegas roadway network. Later, the performance measures are combined to obtain overall benefits associated with a particular scenario. Additionally, a benefit-cost analysis tool is developed to evaluate the prospective projects and the results are compared with other existing methodologies such as California Benefit Cost (Cal-B/C) models. Furthermore, the results of the proposed approach are substantiated using fuzzy logic modeling.

This chapter is organized as follows. The methodology is presented in Section 5.2. Experiments are conducted in Section 5.3 to calculate the benefit-cost ratios for certain projects. Results and analysis are discussed in Section 5.4. Conclusions and recommendations are presented in Section 5.5.

5.2 Methodology

This section describes the modeling and analysis approach. A simulation-based dynamic traffic assignment technique is used to estimate traffic flow related characteristics. Different models are used to estimate multiple performance measures based on the traffic flow characteristics. Section 5.2.1 and Section 5.2.2 discusses the modeling approach and calibration process respectively. Section 5.2.3 discusses the procedure to estimate performance measures.

5.2.1 Network Modeling

DynusT is the DTA model used in this study (Chiu et al., 2010). A Graphical User Interface, NEXTA, was used to generate from the TDM most of the data required by DynusT. Input required by DynusT includes: network characteristics, origin and destination locations, signal control settings, and the time-dependent OD demand. The network characteristics include such data as the number of lanes, link length, saturation flow rates, and speed limits. The majority of this data was extracted from the existing TDM, although some data collection was required to ensure consistency and reflect existing network conditions. The TDM also provided present demand for year 2012 and projected demand for years 2013, 2020, and 2030, based on the current and estimated socio-economic characteristics in the region.

Ideally, the actual signal settings in the field are used in the model. Signal settings for the existing conditions, representing the Base scenario, were provided by the Freeway and Arterial System of Transportation (FAST) of Las Vegas, Nevada. The signal settings for new signals and future conditions were estimated. This estimation typically is expensive and time consuming; therefore, to simplify the process as well as represent likely future conditions, all intersections were modeled as actuated control. A total of 791 signalized intersections were modeled for the Las Vegas roadway network.

Two separate OD demand matrices were imported from the TDM, one for passenger cars and one for trucks. The Las Vegas TDM roadway network includes a total of 1,646 Traffic Analysis Zones. The morning peak-period (6 AM to 9 AM) was modeled using the corresponding three-hour demand. The demand was distributed for every 15 minute time interval within the morning-peak period. Hence, a total of eight demand matrices were used to dynamically load the vehicles into the network. The region-wide demand distribution over two-hour peak period was estimated using the distribution of traffic counts over the same two-hour peak period. Considering the demand profile, it was determined that aggregation of demand was feasible and convenient for computational performance. After aggregation, the number of zones was reduced from 1646 to 696 and the entire model was consistently updated to reflect zoning changes.

5.2.2 Calibration

Once all the input files were generated, the DTA model was used to determine the average network traffic flow pattern for a morning peak-period of a weekday. To assess the difference between the model results and the real-world, simulated link counts were compared to actual link counts collected from FAST. Ideally, there should not be any difference between simulated and actual counts. However, considering the complexities involved in network traffic flow models, a 15% error range was allowed between simulated and actual counts. Initially, only 36% of the counts were within the 15% error range.

To reduce the significant difference between simulated and actual link counts, calibration efforts were conducted. These calibration efforts focused on the enhancement of the time-varying OD matrices using an optimization procedure that minimizes the absolute deviation between simulated and actual link counts (Chiu and Villalobos, 2010). Several iterations of calibration were conducted until at least 85% of the link counts were within 15% error region, as specified by the Federal Highway Administration Traffic Analysis Volume Toolbox III (2004). After calibration, 87% of the counts were within 15% error region.

5.2.3 Estimation of Performance Measures

This section provides a methodology to estimate the performance measures based on the output from DTA model. In addition, the monetary value (in dollars) associated with corresponding performance measure is also discussed. The inclusion of dollar value will help the decision makers in evaluating a scenario or a network corridor for safety improvements. Also, this will benefit in allocating appropriate resources for overall system performance. The estimated performance measures include: Travel Time, Crashes, Emissions, Fuel Consumption and Vehicle Operating Costs.

5.2.3.1 Travel Time

Travel time for a network link is obtained directly from the DTA model. It is assumed that peak hour volume is 8% of the daily traffic based on the local conditions. As a result appropriate daily and yearly factors are used to convert it into annual travel time. A wage rate of $20/hour is recommended to compute the corresponding monetary costs associated with travel time.

5.2.3.2 Crashes

Safety estimations are computed using the ITS Deployment Analysis Systems (IDAS) methodology, developed by the Intelligent Transportation Systems (ITS) Joint Program Office of the U.S. Department of Transportation. This methodology relates volume-capacity ratios to average crash rates. Crash rates for the year 2012 were obtained from Nevada Traffic Crashes Report (NDOT, 2010). The IDAS default crash rates are multiplied by factor to reflect the characteristics of the Las Vegas roadway network. Hourly volume is obtained from the DTA model. Capacity is given by the saturation flow rate times the number of lanes. Volume to capacity (v/c) ratios is computed to determine the appropriate crash rates. The number of crashes is estimated for three types: fatal, injury, and property damage only (PDO). The estimated number of crashes (in million VMT) in a network link for a specific crash type is given by Equation 5.1.

$$C_{lc} = R_c \times L_l \times V_l \qquad (5.1)$$

where,

C_{lc}: Crashes for link *l* for crash type *c*

R_c: Crash rate for crash type *c* (fatal, injury and PDO) in million VMT

L_l: Link length for link *l*

V_l: Number of vehicles on link *l* (hourly)

The total number of crashes is equal to the summation over the entire network of the number of crashes in each link. Comparison between estimated and actual crashes (NHTSA, 2012) suggested that actual fatal crashes were almost 87 percent higher and injury and PDO crashes were 50-60 percent higher than the estimated values. Hence, calibration factors were used to adequately estimate future crashes. To estimate the corresponding monetary cost, the number of crashes in each type is multiplied by cost factors (CALTRANS, 2012) as shown in Equation 5.2.

$$CC_c = \sum_l C_{lc} \times Co_{C_c} \qquad (5.2)$$

where,

Co_{C_c}: Cost factor of crashes for crash type *c*

CC_c: Cost of crashes for crash type *c* over the network

5.2.3.3 Emissions

Emissions play a very important role in the evaluation of transportation alternatives because they are directly related to human health and the environment. Major pollutants from vehicles include carbon monoxide, volatile organic compounds, oxides of nitrogen, oxides of sulfur, carbon dioxide and particulate matter (PM_{10}). This study uses Emission Rates (ER) in gm/mile provided by the California Air Resource Board (2013) and based on the EMFAC 2011 model. These rates are dependent on link speeds determined using the DTA model. The actual speed of any vehicle type is obtained by dividing the distance travelled with the time taken to cross that link. The estimated emissions for each link in the network are given by Equation 5.3.

$$E_{plkv} = \sum_{i=1}^{n_{lkv}} (ER_{kv}^{i} \times L_l \times 1) \qquad (5.3)$$

where,

ER_{kv}^{i}: Emission rate of vehicle type *v* for vehicle *i* during time interval *k*

n_{lkv}: Number of vehicles for vehicle type *v* on link *l* during time interval *k*

E_{plkv}: Emission for pollutant *p* of vehicle type *v* on link *l* during time interval *k* (ton)

The emissions cost for each of the pollutants is obtained using Benefit/Cost models (Cal B/C models) developed by the California Department of Transportation. It is assumed that the emissions cost in the Las Vegas Valley is the same as the cost in the Los Angeles/South Coast region. The monetary value of emissions (dollar/ton) in 2011 is based on the Cal B/C models (CALTRANS, 2012). Thus, the emissions costs for each pollutant are given by Equation 5.4.

$$EC_p = \sum_k \sum_v \sum_l E_{plkv} \times Co_{E_p} \qquad (5.4)$$

where,

Co_{E_p}: Cost factor of emissions for pollutant type *p*

EC_p: Cost of emissions for pollutant type *p* over the network for entire simulation

5.2.3.4 Fuel Consumption

Fuel consumption plays a vital role in the evaluation of investment of transportation projects. Fuel Consumption rates (FC) (in gallons/mile), is obtained by EMFAC 2011 model. These rates are a function of link speeds that are obtained for each vehicle type using the simulation-based methodology. Fuel Consumption for each link in the network is given by the Equation 5.5.

$$F_{lkv} = \sum_{i=1}^{n_{lkv}} (FC_{kv}^{i} \times L_l \times 1) \tag{5.5}$$

where,

FC_{kv}^{i}: Fuel consumption rate of vehicle type *v* for vehicle *i* during time interval *k*

n_{lkv}: Number of vehicles for vehicle type *v* on link *l* during time interval *k*

F_{lkv}: Fuel consumption of vehicle type *v* on link *l* during time interval *k* (gallons)

Based on the 2011 gas rates, gas cost for autos is assumed as $3/gallon and diesel cost for trucks is assumed as $3.4/gallon. Equation 5.6 shows the fuel consumption costs for any link in the network.

$$FC = \sum_k \sum_v \sum_l F_{lkv} \times Co_{F_v} \tag{5.6}$$

where,

Co_{F_v}: Cost factor of fuel consumption for vehicle type *v*

FC: Cost of fuel consumption over the network for entire simulation

5.2.3.5 Vehicle Operating Costs

Vehicle Operating Costs (VOC) depends on vehicle usage. Components that constitute VOC include fuel, oils, tires, maintenance, repairs, and mileage-dependent depreciation (Sinha & Labi, 2007).VOCs plays a vital role in the evaluation of investment of transportation projects because they include fuel and oils which is directly related to energy consumption and the environment. In this study, medium auto and truck costs were used to estimate VOC using Equation 5.7. Average VOC Rates were obtained from Sinha and Labi (2007) and are reported in cents/vehicle mile.

$$VOC_v = \sum_l VOCR_v \times L_l \times V_{lv} \tag{5.7}$$

where,

VOC_v: Vehicle operating costs for vehicle type *v* on link *l*

$VOCR_v$: Average vehicle operating costs rate for vehicle type *v*

V_{lv}: Number of vehicles for vehicle type *v* on link *l*

The above mentioned performance measures are converted to their annual values using daily and annual factors. As a result, the final analysis will be based on annual monetary values associated with the respective performance measure.

The performance measures for years 2012, 2013, 2020, and 2030 is obtained from post processing the DynusT output and converted to monetary values as discussed in Section 5.2. It is assumed that the growth in between the years is linear and an inflation adjusted rate is used to calculate the respective benefits. Finally, all the benefits for future years are converted to present year using discount rate of 7% and added up to obtain total benefits. Similarly, the costs (right of way, construction, maintenance etc.) associated with a particular project is identified and converted to present value using the discount rate to obtain costs. As a result, the benefit-cost ratio is identified for the corresponding project. The entire analysis is coded and converted to an Interface. This interface is modular and the user defines the analysis year. The interface is flexible and it can perform analysis for the complete network or for selected zones/corridors within the network. For multiple alternatives, a zone is selected for each alternative and then the interface is run for that particular scenario to check the differences from the base case. The interface doesn't have the capability to generate results for comparing multiple alternatives simultaneously.

Ideally, for transportation performance management, two types of economic analysis are performed. The first systematic means of comparing highway investments is called life-cycle cost analysis (LCCA) (USDOT, 2013). This method applies the discount rate to the life-cycle costs of alternatives and obtains the desired outcome based on the least cost. Additionally, LCCA is used where the benefits of the possible project alternatives are basically identical. The second means of evaluating the alternatives is benefit-cost analysis, which considers life-cycle benefits as well as life-cycle costs. Benefit-cost analysis reveals the alternative that maximizes the net benefits from allocation of available resources (USDOT, 2013; Merrill et al., 2015). This research uses the benefit-cost analysis technique to evaluate the prospective projects.

5.3 Experimental Set Up

This section discusses two techniques to obtain the benefit-cost ratio for projects in Las Vegas metropolitan area. The first one is the traditional California Benefit Cost (Cal-B/C) model (CALTRANS, 2012) used predominately for the analysis of large scale networks as well as corridors. It is a PC-based spreadsheet model developed by the California's economic analysis branch and consultants. It uses the TDMs that tend to be static and do not represent the dynamic nature of traffic that is available from simulation tools. Cal-B/C can be used to analyze many types of highway construction and operational improvement projects, as well as some Intelligent Transportation System (ITS) and transit projects. This tool has been widely used in the industry to evaluate multiple projects and alternatives. The second one is the proposed benefit-cost tool developed using DTA models such as DynusT. The performance measures are obtained from the simulation model and estimated for the Las Vegas roadway network. In addition, similar monetary values of time, emissions, crashes, fuel consumption, and vehicle operating costs are taken for both the techniques.

5.3.1 California Benefit Cost Model (Cal-B/C)

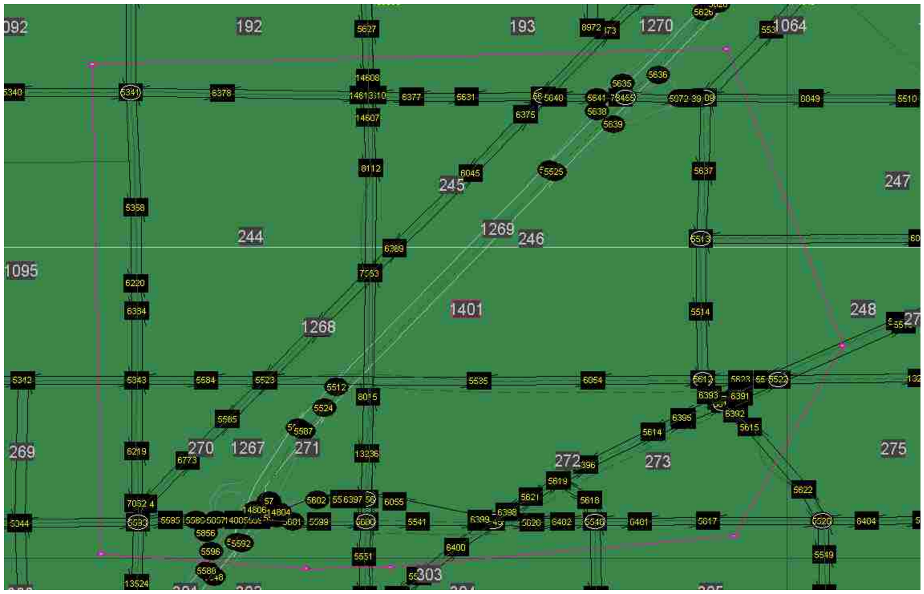
The benefit-cost analyses on three federally funded projects sponsored by the Nevada Department of Transportation (NDOT) were performed using Cal-B/C models. The analyses were formed from existing project reports and NDOT databases that contained project data. The benefit-cost analyses were performed using Cal-B/C with parameter and rate adjustments based on local conditions for Nevada. The following performance measures were considered in the evaluation of benefits and costs.

- Travel Time Savings
- Accident Reductions
- Vehicle Operating Costs
- Vehicle Emission Reductions
- Pavement Roughness
- Project Capital Costs
- Project Operation & Maintenance Costs

These analyses all use a 20-year horizon to enable comparisons among each other. The analyses use a real discount rate of 7% as recommended by the Office of Management and Budget (OMB) Circular A-94 (OMB, 1992).

5.3.2 Proposed Benefit Cost Tool

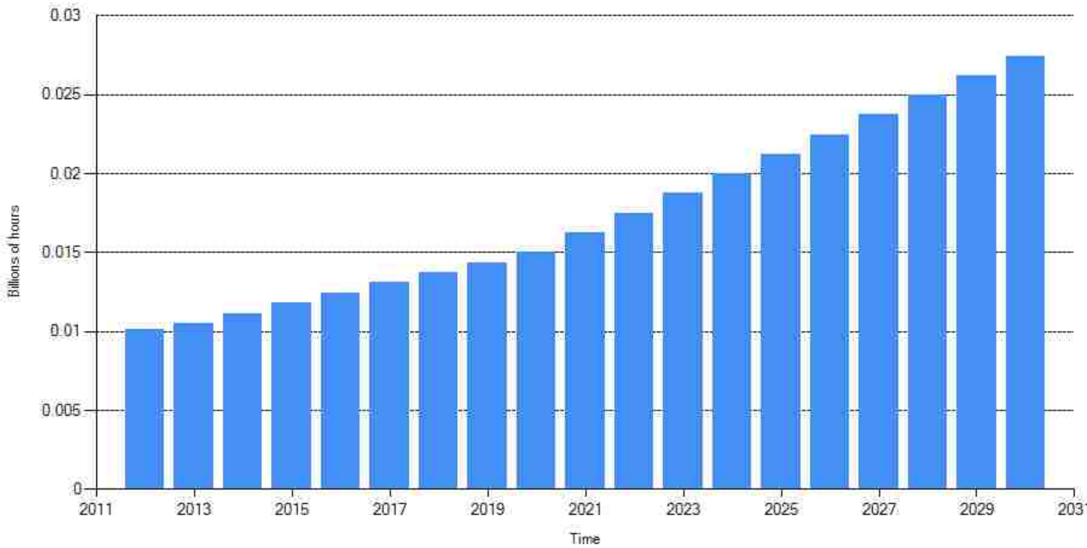
This technique requires selection of a zone near the proposed project and the model is run before and after the improvement. Figure 5.1(a) shows the selected zone with purple colored boundaries for one of the projects in Network EXplorer for Traffic Analysis (NEXTA). It is an interface used to facilitate the preparation, post-processing, and analysis of simulation-based dynamic traffic assignment datasets. The proposed benefit-cost tool uses an interface as shown in Figure 5.1(b). For any project, Figure 5.2(a) demonstrates the trend of performance measures with time on a 20 year time horizon with a discount rate of 7%. The x axis represents the years whereas y axis represents total travel time in billions of hours. Figure 5.2(b) is obtained by clicking any column in Figure 5.1(a) and shows the percent distribution of the costs (in millions) based on individual performance measure.



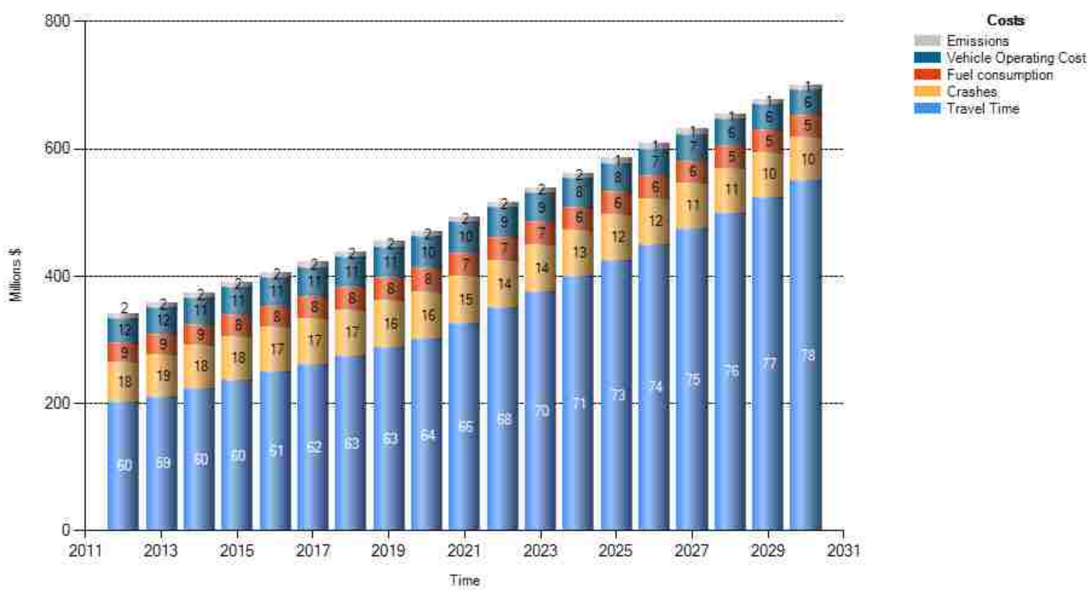
(a)

(b)

Figure 5.1 (a) An example of zone selection within NEXTA, and (b) An interface to estimate performance measures



(a)



(b)

Figure 5.2 (a) Trend of travel time with time, and (b) Percent distribution of costs based on individual performance measures

5.3.3 Proposed Fuzzy Logic Model

This section describes a fuzzy logic modeling approach to prioritize multiple projects. It is an extension of the proposed benefit-cost tool (Section 5.3.2) whereby an attempt is made to devise a technique to incorporate quantitative as well as qualitative performance measures. The performance measures included in this research primarily includes the quantitative variables. Detailed discussion about the theory and techniques are described in Chapter 2. For this particular case, three projects within Las Vegas metropolitan area will be compared based on the cost-effectiveness. The proposed approach will prioritize the projects based on the Sustainability Index (SI) values aggregated over a time frame of 20 years.

The performance measures included in Transportation System (TS) includes travel time, crashes and vehicle operating costs. The rule table defined suggests that if travel time is low, crashes are low, and vehicle operating costs are low; then the performance of TS is high. The performance measures included in Activity System (AS) includes the construction costs, and VMT/capita (Liddle, 2009; Pozdena, 2009; Eckstein, 2011). The literature suggests that VMT/capita is a perfect indicator to measure economic activity with a region. Liddle (2009) studied the historical relationship between VMT, GDP per capita, fuel consumption, and fuel prices. The author used “cointegration” technique and concluded that the U.S. mobility demand has a long-run systemic, mutually causal relationship with income, and gasoline price. Pozdena (2009) used an econometric model and found that VMT is a major driver of GDP. He suggested that a one percent change in VMT per capita results in a 0.9 percent change in GDP per capita within two years, and a 0.46 percent change in 20 years. Eckstein (2011) used time series techniques to test the relationship between VMT and GDP. He found that in times of growth GDP caused growth in VMT, but in downturns, changes in VMT either caused changes in GDP or the relationships were bi-directional. The rule table defined in AS suggests that if construction cost is low, and VMT/capita is low; then the performance of AS is low. The performance measures included in Environment System (ES) includes CO_2 emissions, air pollutants, and fuel consumption. The rule table defined suggests that if CO_2 emissions are low, air pollutants are low, and fuel consumption is low; then the performance of ES is high.

The corresponding performance measures are combined using fuzzy logic techniques described in Section 2.2 to obtain Transportation System Performance Index (TSPI), Activity System Performance Index (ASPI), and Environment System Performance Index (ESPI) respectively. Later, TSPI, ASPI, and ESPI are combined to obtain Composite Sustainability Index (CSI) for a particular year. Figure 5.3 shows the interface to compute the CSI, and in addition, also account for qualitative performance measures. Figure 5.4 indicates that the interface is modular and flexible and has the capability to change the input weights. Figure 5.5 shows the rules and the membership functions for three performance measures to obtain the CSI for a particular year.

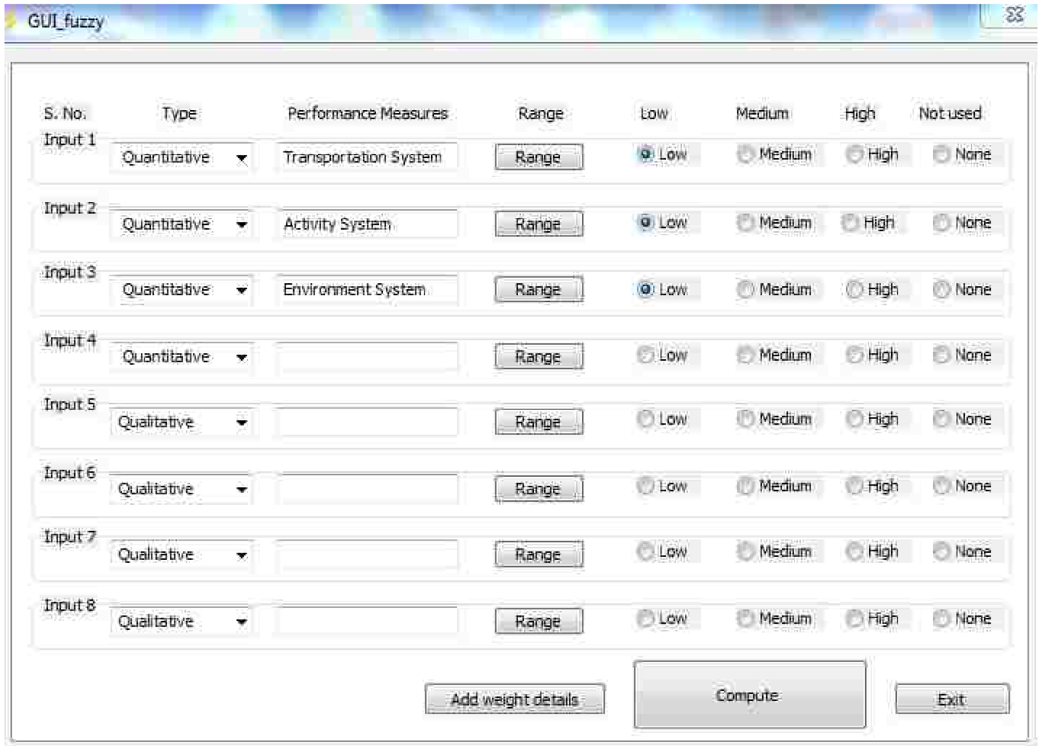


Figure 5.3 A fuzzy interface to compute CSI

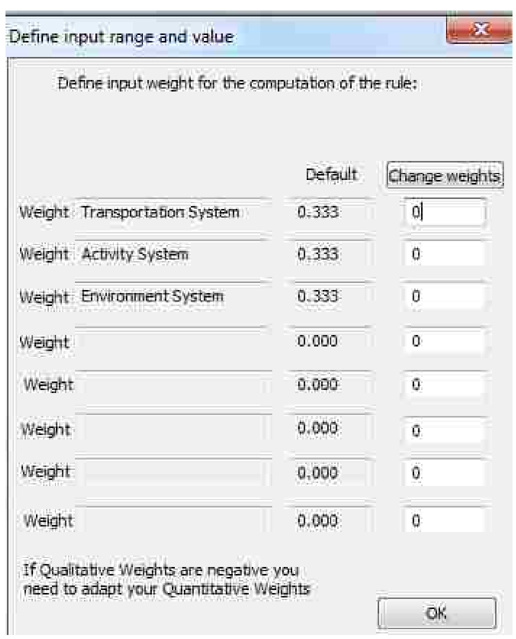


Figure 5.4 An interface showing flexible weighing technique

Figure 5.5 Rules and membership functions to compute CSI

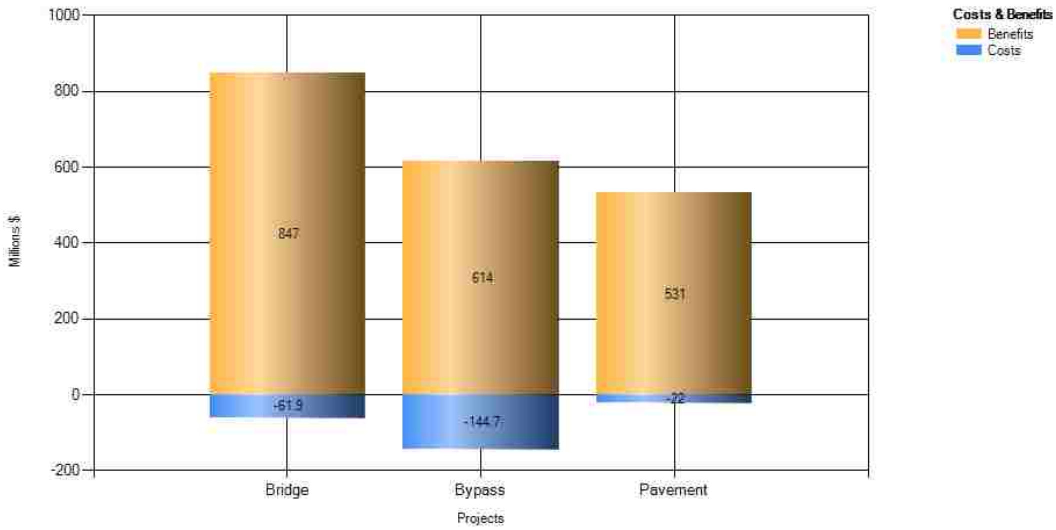
5.4 Results and Analysis

The comparative analysis of the results of the benefit-cost ratio obtained from the proposed tool and the Cal-B/C models is shown in Table 5.1. Ideally, from a decision maker's perspective, projects are prioritized by their net present value of benefit-cost ratios. The higher the ratio, the more important is the project. For Cal-B/C model, the priorities are in following order: Project 1>Project 3>Project 2 whereas for proposed tool, the priorities are as follows: Project 3>Project 1>Project 2. In addition, the analysis shows that the benefit-cost ratio for Project 1 has the minimum variance for the two techniques.

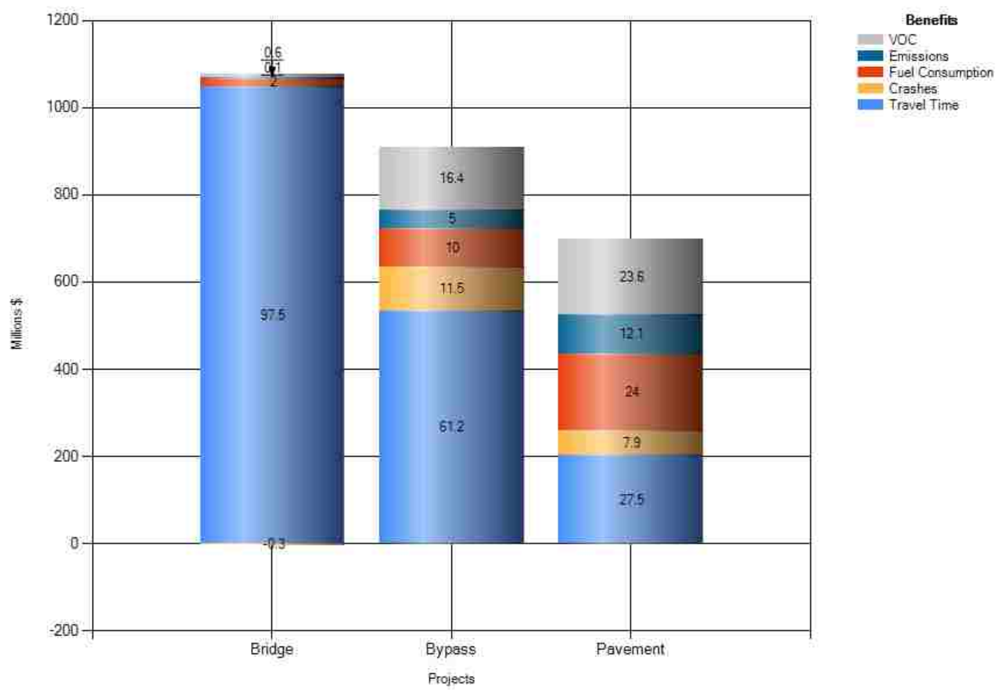
Table 5.1 Summary of the results of benefit cost analysis for multiple projects

Project No.	Project Description	Type	Benefit-Cost Ratio from Cal- B/C models	Benefit-Cost Ratio from proposed tool
1	North 5th Street Super Arterial Phases 1C & 1D: Carey to Cheyenne	Bridge Construction	12.60	13.68
2	Boulder City Bypass Phase 1: Foothills Drive to US-93/US-95 Interchange	Bypass/ New Interchange	0.90	4.25
3	US 93 Pavement Rehabilitation & Truck Climbing Lanes	Widening/ Pavement Rehabilitation	8.30	24.17

Figure 5.6(a) shows the benefit-cost analysis for the three projects based on the proposed tool. The x-axis indicates the type of project and the y axis represents the associated dollar amount in millions. The benefits associated with each project are compared with the base case and the difference is shown on positive y-axis. The cost associated with the project is considered as negative and is shown on negative y-axis. Figure 5.6(b) shows the percent distribution of total benefits based on individual performance measures.



(a)



(b)

Figure 5.6 (a) Benefit-Cost Analysis for projects based on proposed tool, and (b) Percent distribution of benefits based on individual performance measures

The results from Table 5.1 indicated that existing Cal-B/C models underestimate the benefits associated with the project. The proposed tool provides an alternate technique to estimate the benefit-cost ratio. The source of the differences is due to the differences in methodology (DTA vs TDM) as well as input data (volume and speed data). DTA typically constrains the v/c ratio to 1, while most TDMs have fewer constraints. The maximum v/c parameter in Cal B/C models is 1.56 to obtain 5 MPH speed estimates for a free-flow speed of 70 mph (CALTRANS, 2012). In addition, the computation of travel time in both the models is a major factor in increased benefits for the proposed tool as compared to Cal B/C models. The proposed tool uses the actual travel time for any vehicle based on the real travel speed whereas the Cal B/C model uses average speed of the vehicles for analysis. The results also substantiate the use of DTA models for evaluating projects in a cost effective manner.

For the proposed fuzzy logic model, similar technique is used (Section 5.3.3) to compute the CSI for future years for all three projects and a trend is obtained as shown in Figure 5.7.

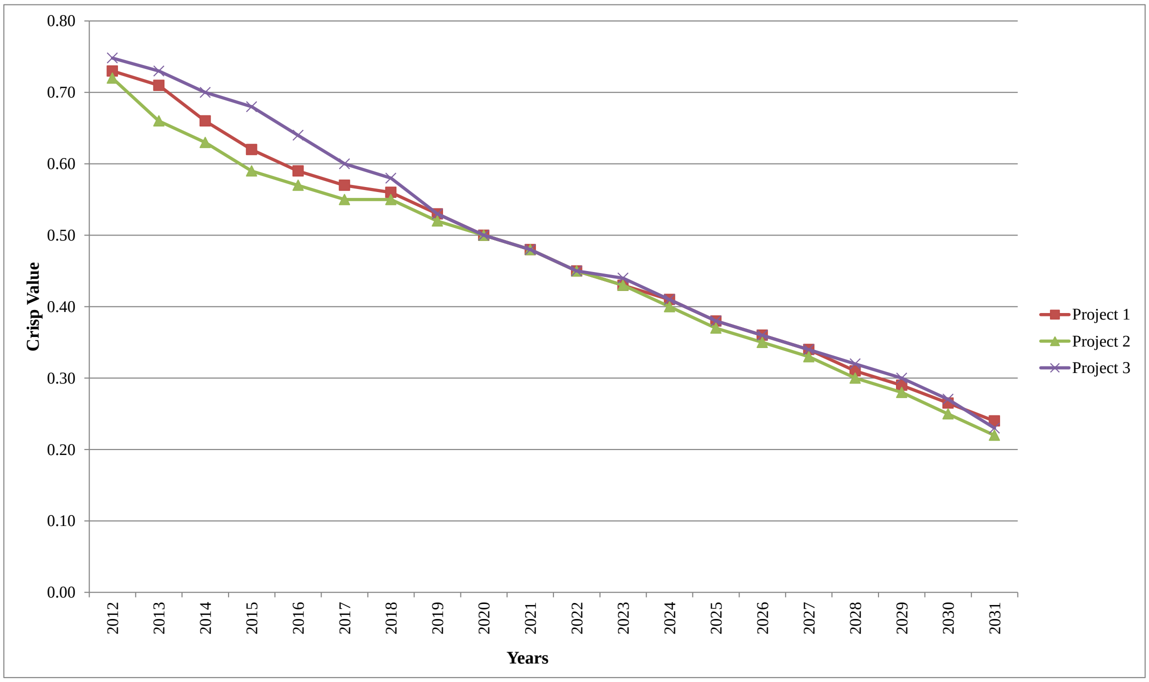


Figure 5.7 Trend showing Composite Sustainability Index over 20 years

To get an average value, the area under each curve is calculated and a final crisp value is obtained as shown in Table 5.2, also known as Sustainability Index (SI).

Table 5.2 Fuzzy values, Area and SI for Project 1, Project 2, and Project 3

	Project 1 (P1)	Project 2 (P2)	Project 3 (P3)			
Year	**Fuzzy values P1**	**Fuzzy values P2**	**Fuzzy values P3**	**Area P1**	**Area P2**	**Area P3**
2012	0.73	0.72	0.75			
2013	0.71	0.66	0.73	0.72	0.69	0.74
2014	0.66	0.63	0.70	0.69	0.65	0.72
2015	0.62	0.59	0.68	0.64	0.61	0.69
2016	0.59	0.57	0.64	0.61	0.58	0.66
2017	0.57	0.55	0.60	0.58	0.56	0.62
2018	0.56	0.55	0.58	0.57	0.55	0.59
2019	0.53	0.52	0.53	0.55	0.54	0.56
2020	0.50	0.50	0.50	0.52	0.51	0.52
2021	0.48	0.48	0.48	0.49	0.49	0.49
2022	0.45	0.45	0.45	0.47	0.47	0.47
2023	0.43	0.43	0.44	0.44	0.44	0.45
2024	0.41	0.40	0.41	0.42	0.42	0.43
2025	0.38	0.37	0.38	0.40	0.39	0.40
2026	0.36	0.35	0.36	0.37	0.36	0.37
2027	0.34	0.33	0.34	0.35	0.34	0.35
2028	0.31	0.30	0.32	0.33	0.32	0.33
2029	0.29	0.28	0.30	0.30	0.29	0.31
2030	0.27	0.25	0.27	0.28	0.26	0.29
2031	0.24	0.22	0.23	0.25	0.23	0.25
SI				**8.94**	**8.68**	**9.20**

The SI value will be used to compare and evaluate the three projects. The higher the SI value, the better is the corresponding project. Based on the analysis, the priority of the projects is Project 3>Project 1>Project 2. This coincides with the ranking of projects from proposed benefit-cost tool discussed in Table 5.1.

This field of benefit-cost analysis requires lot of input from experts. This serves as a criterion for decision makers to evaluate projects. Therefore, fuzzy logic is appropriate modeling technique as it allows to define the variables in linguistic terms. The sustainability analysis using fuzzy modeling approach clearly has advantages as it provides a framework to incorporate both quantitative as well as qualitative variables.

Other researchers can build on this framework and prepare robust models that incorporate all sustainability considerations.

5.5 Conclusions and Recommendations

Existing state of the art techniques concentrate primarily on estimation of performance measures using static approaches. However, to accurately estimate the traffic flow characteristics, dynamic models are predominately used by researchers. This research proposed a comprehensive methodology to estimate performance measures using DTA models and evaluate projects. Numerical experiments were conducted to evaluate three projects in Las Vegas Metropolitan area. A comparative analysis with the existing Cal-B/C models revealed that the proposed tool provides an alternate ranking of projects. In addition, the results also indicated that Cal-B/C models underestimate the benefits associated with the projects. The major contribution of this research is development of a framework to estimate sustainability indices for the evaluation and prioritization of transportation projects. Projects are prioritized and ranked based on the sustainability index values. The experiments showed that the proposed methodology is robust and it provides a necessary framework to decision makers to evaluate multiple projects in a timely and cost-effective manner.

CHAPTER 6

CONTRIBUTIONS AND RECOMMENDATIONS

6.1 Summary

This dissertation presents a comprehensive analysis to develop a decision support framework for the planning of sustainable transportation systems. The proposed framework seeks to incorporate sustainability considerations at the macro- and micro-level.

At the macro-level, performance measures are identified for the entire U.S. The current research adopted a holistic approach that computes Performance Indices for a system of systems (SOS) including Transportation, Activity and Environmental systems. The performance indices are combined to obtain a Composite Sustainability Index. Considering the complexity, vagueness, nonlinearity, qualitative, and incomplete information characterizing the quantification of the Performance and Composite Sustainability Indices, a fuzzy logic approach was used to compute these indices. The analysis is performed by taking 23 year data for U.S. The results indicated that the Transportation and Activity systems both follow positive trend over the years whereas the Environmental system follows an overall negative trend. This is evident as continuous economic growth and transportation activities require additional resources from the Environmental system. The results are based on the performance measures that are considered in this study. Adding or removing performance measures are expected to change the results and associated conclusions.

Recently, sustainability has become a very important research area in transportation because the resources required to operate and preserve the system are limited. The existing practice and technologies are not prepared to deal with the expected scarcity of resources. A meaningful consideration of sustainability in transportation requires factoring the intricate dependencies between the transportation, economic, and environmental systems. A vast intellectual effort is being invested to try to understand these interdependencies. A primary challenge is to capture the behavior and interdependencies of such systems over time. This research attempts to build dynamic models to capture the interdependent behavior of transportation, economic, and environmental systems. Non-linear modeling techniques, Predator–prey models, were utilized to capture the nominal behavior of all the three systems. The results indicated periodic behavior with a phase lag for the performance of transportation and the activity system while the performance of environment system decayed with time. Furthermore, policies were evaluated for investment in energy efficient technologies, and the effect of the policy on the three systems was discussed. The results showed that it is possible to formulate an optimal control to achieve the desired target. The numerical results are based on actual parameters and they are presented to illustrate the long-term trends of the three systems. This helps the decision makers to understand and formulate policies for the growth/decline in the three systems in the future.

Considering sustainability at a macro-level is important to develop policies to conserve resources, study global climate change effects, and reduce the carbon footprint. However, individual geographic regions are significant contributors to the overall changes in the macro environment. As a result, it becomes necessary to study the effects of transportation, activity and the environmental systems on the overall sustainability for a particular region. To perform micro-level analysis, sustainability considerations were evaluated within regional systems including large metropolitan areas. A simulation-based approach was developed to estimate performance measures, and later the performance measures were combined to obtain sustainability indices. Three transportation projects in the Las Vegas metropolitan area were evaluated using sustainability index values. The results indicated that the proposed framework provides an alternate method to rank and prioritize projects. This research provided numerical models, tools and techniques to understand the dynamic nature of sustainability from both macro as well as micro level perspective. Overall, this research improves the understanding of sustainability by evaluating multiple systems simultaneously. Planning and operational policies for the sustainability of the Transportation, Activity, and Environmental systems can be developed based on the gained insights from this research. For example, the effect of implementing policies that require long term capital expenditures on the three systems can be studied. This also gives an indication of when and how the policies be modified to reduce resource consumption while sustaining growth and economic development.

6.2 Contributions

The policies developed in the past have shown positive effects but significant efforts from a long term policy perspective are needed to save the Environmental system from further degrading. **The first contribution of this research is the development of a framework to generate sustainability indices for policy making considering,**

explicitly, multiple interdependent systems. The sustainability indices are based on historic data and hence long term trends can be generated to help decision makers to develop appropriate policies for sustainable growth. The indices provide a reasonable indication of the performance of any system as compared to historic trend. In addition, the indices can help to promote and develop policies such as use of non-motorized modes of transportation, transit oriented developments, use of compressed natural gas as an alternate fuel, usage based VMT fee, and investment in energy efficient and green technologies.

The results also indicated that the transportation and activity systems follow a lead-lag phase behavior whereas the trend for the environmental system decreases with time. This has been verified with the periods of growth and recession within the economy. However, to the best of the author's knowledge, **no previous study has attempted to study the dynamical interactions between these three systems. The second contribution of this research is a detailed analysis to understand the dynamics of the three interdependent systems - Transportation, Activity and Environment systems. Multiple insights were obtained from this research.** The techniques learnt can be applied to perform multi-city network modeling through the concept of interconnected networks. The movement of trade, traffic flow, economic activity and emissions between multiple cities can be modeled. **The third contribution of this research work is the development of control mechanisms for the design of sustainable transportation systems. Investment decisions were derived from the design.** For example, a policy scenario regarding investment in energy-efficient technologies and their effects on the systems was developed to make investment decisions over time. This is helpful for decision makers to anticipate the amount of investments needed in the future for a particular policy. Similarly, multiple policy scenarios can be created and investment trends can be generated.

Additionally, the proposed work also provides an alternate cost-effective framework to decision makers for transportation improvements. **The fourth contribution of this research is development of a framework to estimate sustainability indices for the evaluation and prioritization of transportation projects**. Projects are prioritized and ranked based on the sustainability index values. The greater the sustainability index value, the higher is the project priority. This provides a comprehensive mechanism to prioritize projects beyond traditional techniques prevalent within the industry.

6.3 Limitations

There are certain limitations associated with this research. These include:

1) This research is primarily focused on addressing the direction and movement of performance indices without quantifying the impacts of policy decisions on performance measures. Future research can look into this direction.
2) This dissertation introduces the concept of threshold limit and its numerical value is not estimated here. This computation of threshold limit has been estimated and successfully used in various other disciplines such as hydrology, geography, ecology etc. However, detailed and thorough analysis is required to estimate the threshold limit in the context of sustainability.

3) This dissertation used triangular membership functions in the fuzzy logic modeling for the performance measures and indices. However, other membership functions such as trapezoidal, gaussian, polynomial etc. could be used to check the differences in the results.
4) While this dissertation provided a framework to rank and prioritize projects more projects could be analyzed to evaluate the robustness of the framework.

6.4 Recommendations

Although numerical methods (fuzzy logic, dynamic modeling, and control techniques) have performed satisfactorily in understanding the relationships between Transportation, Activity and Environmental systems, future work is desired in terms of their ability to predict long-term trends. The field of sustainability and the interactions between the physical systems are constantly evolving as researchers and scientists continue to explore new ideas, develop new techniques, and create new policies. As a result of this dissertation, several future research directions arise and could be investigated. These include:

1) This dissertation identified the performance indices based on a limited number of performance measures. Follow-up studies could focus more on selecting the more relevant performance measures to provide a comprehensive and accurate analysis.
2) This dissertation studied the interactions between the Transportation, Activity and Environmental Systems using dynamic modeling techniques. The potential of such techniques could provide useful information to researchers in enhancing non-linear models for better analysis of sustainable systems. As a result, this

model can be used as a starting point to understand the behavior of system of systems.

3) This dissertation developed optimal control models for investment in energy efficient technologies. It is emphasized that the methodology discussed here will be helpful to decision makers to make optimum decisions. Extending the scope through different policy examples could provide further understanding to implement such techniques in various other fields.
4) While this dissertation evaluated quantitative performance measures to calculate sustainability indices, qualitative performance measures (comfort, aesthetics, livability etc.) should also be considered for future analysis.
5) Several new approaches that includes multi-agent (NetLogo), and system dynamics modeling could be used to perform microscopic modeling; and further open doors to research in multidisciplinary fields.
6) It is also recommended that similar macroscopic and microscopic models be developed for various locations in U.S. and other countries, and an effort be made to further understand the interactions within these models as a function of the space and time.

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