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Quantifying economic benefits for rail infrastructure projects

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QUANTIFYING ECONOMIC BENEFITS FOR RAIL INFRASTRUCTURE PROJECTS

by

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ABSTRACT

Investment in rail infrastructure is necessary to maintain existing service and to cater for future growth in freight and passenger services. Many communities have realized the importance of investment in rail infrastructure projects and set up goals and visions to achieve economic development through investing in such projects. Due to limited funds available, communities have to select a single or very few projects from a variety of projects. It is very critical that right projects must be selected at the right time for a community to realize economic development. The limited methods for quantifying the economic benefits to the stakeholders often cause a problem in the selection process. Most of the conventional methods focus mainly on the economic impact of the project and ignore the metrics that convey the economic impacts in meaningful ways to the key stakeholders involved. This leads to uncertainty in the project selection and planning process and often leads to failure in achieving the goals of the project.

This study aims to provide a mathematical framework that quantifies economic benefits of investment in rail infrastructure projects in meaningful ways to the key stakeholders through three different approaches, namely, Leontief-based approach, Bayesian approach and system dynamics approach. The Leontief-based approach is the easiest of all the three approaches provided that historical data is available. Bayesian approach is also very beneficial as it can be used by coupling small data with surveys and interviews. Also, system dynamics model is very useful to conduct qualitative analysis, but the quantitative analysis part can become very complex.

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1. INTRODUCTION

Rail infrastructure contributes to the economic vitality of an economy. It moves both, the public and freight, and hence, in combination with the rest of the infrastructure industry, has a strong impact on the society and the private sectors. According to the US chamber of Commerce, $1 spent on infrastructure construction leads to approximately $1.92 direct and indirect economic output [1]. It has also been shown that for every one billion dollars of investment in infrastructure, as much as 20,000 new jobs can be created [1]. The focus of this work is to quantify economic benefits realized from investment in rail infrastructure projects. For economic and community development selecting the right project at the right time is a must. This selection process is significantly hampered by limited methods to quantify the economic benefit to a stakeholder.

This work aims at developing a mathematical framework/methodology that uses metrics in a way that conveys economic impact in meaningful ways to the stakeholders. Communities often have to select a single or very few projects from a vast pool of ideas due to the limited funds available for investment. To avoid any uncertainties or fluctuations in the availability of funds, additional investment portfolios need to be created, and innovative approaches and public private partnerships should be encouraged. The increasing interest in integrating sustainable development[1] into decision-making processes requires the integration of social and technical parameters while quantifying benefits is essential. Also, similar to other developmental efforts, sustainable development strategies can change with time, so to account for the changes over time and approach sustainable development, the decision-making tools chosen must be flexible. For an integrated approach that involves both the economic and end-user factors, the process becomes a multi-objective decision making process– that is to say, in such

[1] Sustainable development refers to the type of development that improves the quality of life and leads to economic growth while preserving and enhancing the natural environment [2]. The idea of sustainable development was included to the new mandate of International Union for Conservation of Nature (IUCN) in 1969 and dates back more than 40 years [3]. Although, the idea of sustainability has been into existence for a long time, organizations focuses on easy to measure goals and impacts [4] while ignoring difficult to measure social impacts and public acceptance [2].

decision processes, there will be the need to address multiple objectives simultaneously. These are complex decision processes. To address such complex decision processes, the economic and end-user factors can be divided into two categories: decision items and objective functions. Decision items are the factors over which the decision makers of a project have direct control. The objective functions are the ultimate goals to be achieved by a project. Thus, identifying the main stakeholder groups, the benefits to each stakeholder group and studying the interdependencies among them is vital to a thorough understanding of the impact of modifying or expanding existing rail road infrastructure. Based on the above discussion, this project proposes three possible methods to quantify the benefits of investing in railroad infrastructure.

Investment in railroad infrastructure will help support national freight and passenger capacity goals. With the development of the railroad infrastructure, the on-road traffic would also decrease. The main stakeholders in any railroad project are considered to be the community (residents) in which the project is situated, the governmental entities through which, or in which, the project is situated, the railroad, the railroad's customers, the suppliers and contractors to the railroad and other entities concerned with broader environmental impacts, as well as all parties that could be negatively impacted by the project. The benefits and costs associated with each of the stakeholder groups need to be evaluated and the interdependencies among them studied.

To illustrate the concepts laid out in the preceding paragraph, construction of a new railroad bridge will be used to particularize the constructs. A new railroad bridge will add to transportation options available to the general public as well as the shipping/freight industry and may help reduce on-road vehicular traffic and also reduce the GHG loads from trains sitting on the sidings along with other economic and non-economic benefits. Any change in travel cost, accessibility, and reduction in travel time due to this modification will affect the public sector. Further, increases in the number of jobs, tax revenue, utility revenue, etc. are possible metrics that could affect government sector decision-making and policies. These objectives (benefits) contribute to the technical aspect of the impact of modification in rail infrastructure. Another technical factor involved in this system is the capacity of the rail corridor. Corridor capacity may be impacted by both infrastructure improvements and operating practice improvements.

In this study, the focus is on infrastructure investments that may improve corridor capacity. Improvements in corridor capacity may lead to reduced transit times, reduce costs, improved transit consistency, etc., all of which may beneficially impact private sector stakeholders, as well as the public and community sectors because of such things as reduced vehicular congestion, reduced GHG, etc.

Conventional decision-making processes in the infrastructure industry generally rely on cost-benefit analyses and impact assessments, and are thus, unable to address future transportation system challenges completely [5]. Therefore, it is imperative to adopt methods that are capable of acknowledging the diverse interests of all the stakeholder groups. The evaluation methodologies to study an infrastructure project can be broadly divided into two categories - linear and non-linear. Whether to adopt a linear or non-linear methodology can only be determined after the identification of factors involved in the particular project has occurred, in addition to identifying the interdependencies among the factors. These interdependencies help in determining which possible evaluation methodologies are best suited to a project. In addition to the relationship between the factors, the availability of data and other resources and the time constraint for evaluation affect the decision on choosing an appropriate evaluation method.

This report outlines three methods to quantify rail benefits, namely Leontief input-output model, Bayesian approach and System Dynamics (SD) approach. These methodologies have previously been used in the field of construction and infrastructure projects, and are well understood in terms of strengths and limitations. Details on the use of these methods in various industries are given in the following literature review-section. Following that are the procedures for each approach with a sample calculation. Concluding remarks and references can be found towards the end of the report. The possible metrics for railroad infrastructure investment projects used to develop the mathematical framework are shown in Table 1.1.

Table 1.1 Possible Metrics for Rail Infrastructure Investment Projects

Decision Variables	- Money to be invested - Number of workers to be hired
Objective variables	- Number of Jobs Created - Increase in Tax Revenue - Increase in Local Business Revenue - Increase in Utility Revenue - Decrease in Passenger's Travel Time - Decrease in Travel Cost for the Passengers - Decrease in Costs Accumulated by Shippers - Decrease in Costs Accumulated by Receivers - Increase in corridor capacity - Increase in level of service - Increase in Accessibility - Development of Local Economy - Potential for New Business Opportunities

2. LITERATURE REVIEW

2.1 LEONTIEF-BASED APPROACH

The Leontief input-output model was developed by Professor Wassily Leontief in the 1930s [6]. The model, originally applied to economic systems was based on the assumption that each type of industry had two types of demands, the internal demand and the external demand. Each industry makes a homogenous product, and the input ratio for the production of an output is fixed for an industry was the other assumptions. Based on these assumptions the economy model was depicted as a set of different linear equations [6]. The Leontief input-output model studies the interdependencies among the various industries involved. It shows how the outputs from one industry affect another industry by acting as an input to that industry. This approach was initially developed to study the interdependencies between different sectors of the economy. The Leontief model can tell us about the productivity of an economy, i.e., it is possible to get the production based on the demand levels of an economy. The model uses a system of linear equations to get the desired output variables. A simple system of linear equations can be solved using matrix algebra. The Leontief model is of two types, the open type and the closed type. A closed economy model assumes that no goods enter or leave the economy. On the other hand, in an open system, an economy has to meet demands outside of itself, i.e., goods may enter or leave the economy. Based on this approach, Leontief represents the world economy as a system of interdependent processes. He uses the input-output model to elucidate the world economy. He explains that an output for one sub-system would require a particular amount of input, which could be the output of some other sub-system and so on. Leontief divided the world economy into two parts, i.e., developed and less developed regions and further divides these into sub-systems. Using the Leontief approach provides a framework to organize and assemble data needed to describe the structure of world economy, and finally use of this model predicts the behavior of the economy in the future [7].Due to its simplicity and systematic approach, the Leontief input-output model can be applied to systems other than economy models, such as infrastructure, risk management, etc. Farooq et al. [8] make use of the Leontief input-output model to study the impact of intelligent transportation system (ITS) on the economy of the state of Michigan. They incorporate the effects of ITS in the transportation industry and designed a model to study its effects. They calculate the growth correlation factor for each industry using the Leontief approach and use it in a RIMS II input-output table to calculate the economic impact of ITS on other industries. Using their model they find that ITS will help to increase the number of jobs for all industries and the output per dollar [8]. Haimes and Jiang [9] develop a Leontief-based infrastructure output-input model to study the interdependency between various critical infrastructures as well as the interconnectedness within each critical infrastructure. Through this model they also captured the risk of inoperability of various critical infrastructures due to failure of one or more of the critical infrastructures or due to some kind of natural disaster. The Leontief input-output model can be further extended into an inoperability input-output model (IIM). Yakov et al. [10] studied the IIM to study interdependencies, initial disruptions, and the resulting ripple effects. Santos [11] uses the Inoperability Input-output Model (IIM) that is based on Leontief's input-output model to study the ripple effects of disruptions on interdependent systems. By using the IIM model, Santos analyzes the effects of 9/11 on the demand for air transportation and its ripple effects on other sectors. This paper provides a framework to identify the primary sector that is most affected due to a catastrophe such as 9/11 and the ripple effects that such an adverse event has on other sectors which are economically interdependent with the primary sector. The model proposed in this paper can be applied to study the effect of any adverse event on the economy of a system by understanding the underlying interdependencies [11].

Wang [12] uses Leontief input-output model to construct a framework for analyzing the relationship between industrial and transport structure. Wang based this study on China where the industry is divided into three sectors namely, primary industry which includes agriculture, forestry, animal husbandry, fishery and farming and their services, secondary industry which includes mining, manufacturing, electric power, gas and water production and supply industry and construction industry, and tertiary industry which includes all other industries except those included in the primary and secondary industries. The five modes of transportation are described as railway, highway, water transport, air transport and pipeline transport. Wang uses the Leontief approach to conclude that as the three industry sectors would develop there would be rise in the demand of railway, highway and water transportation modes for the secondary and tertiary industries which would lead to the development of national economy [12]. Lin et al. [13] study the impact of earthquakes on the industrial chain in Taiwan. They simulate two earthquakes and study their impact using the Leontief input-output model. After studying the correlation between various industries, the authors are able to use the Leontief model to find out the effect of an earthquake on the different sectors of the industry. They find that the losses due to one of the earthquake are much greater than the other as the former happens in an area where the infrastructure for manufacturing is located. Hence, the output value and the repercussion effects for the former earthquake are much higher than in the latter.

In the above references, the Leontief approach has been used to identify and study the interdependencies among various variables. This demonstrates that the Leontief approach is a versatile one and can be applied to a variety of different systems. Therefore, it can also be extended and applied to the railroad infrastructure investment project.

2.2 BAYESIAN APPROACH

A Bayesian network model is a probabilistic graphical model that represents the probabilistic relations between variables dependent on each other. It is a multi-objective evaluation method and is very useful when decision criteria are to be established. A Bayesian network is a decision network that systematically and logically joins the decision items to the objective functions via some evaluation criteria. They enable an effective representation and computation of the joint probability distribution (JPD) over a set of random variables [14]. Bayesian network models enable decision-makers to eliminate suboptimal solutions to arrive at the most profitable investment option in the socio-technical framework [15]. Correctly establishing a Bayesian network is critical to this method.

This approach finds applicability in the field of economics, engineering, and bioinformatics, etc [16]. Bayesian network methods have also been applied to supply chain problems. According to Arasteh, Aliahmadi and Omran, [17] all businesses involve management of goods, funds and information, that move through the supply chain. This makes the whole system complex and dynamic with interconnectedness among various parts of the business. The use of Bayesian network models can help identify strategies to reduce or eliminate the effect of disruptions that might occur in a business, thereby increasing overall reliability [17]. Luoto et al. [18] used Finnish data to study the effect of investment in infrastructure on the economy and conclude that investing in infrastructure has a strong positive effect on output growth over the long-run. Xiaocong and Ling [19] established a risk management decision support system using a Bayesian network approach that is effective for intuitive and real time decision-making in risk management. They have used the Bayesian technique to identify the causes of risk and analyze the factors that cause the risk in a simple, probabilistic, independent and easily recognizable way. Their model helps study the effect on the project due to a sudden risk event and allows decisions to be taken to manage the risks. Zhu et al. [20] use Bayesian networks to construct an intersection safety evaluation index system. They make use of experts' opinions to quantify various qualitative variables involved. They ask for index values from different experts for a similar situation and then aggregate the experts' opinions using Bayesian network analysis. Zhu et al. divide the safety level of the intersection into five levels and test their model to diagnose and analyze the safety at an intersection even without the presence of any accident statistical data. They also develop a methodology to obtain indices for some other variables even without certain experts' opinion. Jha [21] makes use of the Bayesian approach to predict the likelihood of terrorist attacks at critical infrastructure facilities. Using dynamic Bayesian networks, Jha develops a reliable prediction model and analyzes the relevance of available intelligence to develop a terrorist attack prediction model. Cho et al. [22] develop a probabilistic model to predict infrastructure maintenance using Bayesian network analysis. This model helps to predict the damage that would occur and the maintenance budget that would be required for bridge components. Through this model they have developed a mechanism to predict the future performance of the infrastructure and the budget that would be required to maintain such complex infrastructures [22].

The Bayesian network is a directed acyclic graph that consists of two sets: set of nodes, and a set of directed edges. The edges represent direct dependencies between the nodes and are drawn by arrows between them [23]. The nodes are connected according to the reasoning direction of decision makers [24]. The relationship between each pair of connected nodes is expressed in the form of probability distribution that encapsulates the decision makers' experience [24]. The nodes involved can further be divided into three sets: decision nodes, evaluation nodes and objective nodes, representing the decision items, evaluation criteria and objective functions, respectively. The decision items and objective functions are as defined previously in introduction. Evaluation criteria are the connecting links between the decision items and objective functions. Evaluation criteria measure effectiveness of the decision in achieving the ultimate goal or objectives. The edges/arrows determine the parent nodes for each node. The parent node(s) for evaluation criteria will be from among the decision items, and the parent nodes for the objective functions from among the evaluation criteria.

The decision items are determined by the decision makers' experience or by conducting a survey among a panel of experts and selecting the highest rated items. The expert panel is chosen in a way so as to include knowledgeable experienced people from all the stakeholder groups affected by the project [25]. The expert panel must be carefully chosen to include people that acknowledge the diversity of the socio-technical elements involved. Following the decision items, evaluation criteria are also selected in a similar manner. The objective functions are then put together with the other nodes to complete the network. The next step is to determine a set of values for each decision item. The possible values for the decision items are decided based on the decision makers' experience and the resources available. A similar set of values for the evaluation criteria is determined. This set of values is based on the possible outcomes of a project and the way it will determine the ability of the decision items to help achieve the desired goal. For the objective functions, a rating scale is established on which the success of the project can be determined. This has also been shown in [26], that multi-objective decision making process involves simultaneously making decisions on various items, achieving a trade-off among probabilistically dependent items, and also to provide enough knowledge to build a realistic model. Beck and Katafygiotis [27] provide a Bayesian framework that can be used to update a model. They argue that using their proposed model more accurate response predictions can be made. According to them, a model containing a large number of data points with relatively small number of variables with uncertainty can be updated accurately using a Bayesian statistical technique. Predicting the deteriorating conditions of the bridge might not be accurate by just analyzing the inspection data as they might have as the limitations of the methods used to measure data and the error in measurement is not taken into account [27]. Enright and Frangopol [28] predict the future of the bridges in a better way by making use of Bayesian techniques to incorporate engineering judgment along with the inspection data.

Di Giorgio and Liberati [25] divide the Dynamic Bayesian Network in three levels i.e., atomic events, propagation and services level based on their relation with the various critical infrastructures. They also highlight three different types of analyses that can be performed on the resulting dynamic Bayesian network, i.e., reliability analysis, adverse events propagation analysis and failure prediction analysis. Xie and Ng [15] establish a framework to evaluate if the project is able to meet the interests of the key stakeholders. They make use of an example from a case study to determine which of the scenarios would be most suitable in a public-private partnership and identify and highlight the various factors that would be most critical for the success of the project and also to satisfy the stakeholders. Pang et al. [29] establish a framework on Economic Early Warning based on Bayesian network models to counter the effects of assumptions that are set, for example, the cause variable will only affect the effect variable and will not itself be affected by the effect variable. They use the Bayesian approach so as to consider the complex variables and the interdependencies between these variables to construct a cause and consequence diagram to overcome this problem. Dorner et al. [30] develop a multi-objective model using the Bayesian approach to analyze multiple objective functions using an already existing environmental model that has a single problem domain. . This property of the Bayesian models is critical as most of the projects have multiple objective functions. All of these properties of Bayesian models lend themselves to analysis of transportation infrastructure investments, and more particularly, investments in railroad infrastructure, since as described previously in the discussion of socio-technical frameworks, railroad infrastructure is clearly shown to have multiple stakeholders with multiple objectives.

2.3 SYSTEM DYNAMICS APPROACH

System dynamics (SD) is a methodology to understand and analyze the dynamic nature of complex systems. This approach is normally used in systems where there are a large number of variables involved and there are complex relations between them. This approach makes use of qualitative and quantitative models to understand how the interdependent variables act in a system over time [31]. Feedback loops are used in a system dynamics model that makes this approach unique. A feedback loop is a loop connecting two or more variables such that a change in one variable would bring about a change in the other. Feedback loops are of two types, namely, positive and negative loops. Positive loops are also known as reinforcing loops which means that a change in the value of the variable in the loop would induce a similar change in the other variable, i.e., if one variable increases, then the other would also increase and vice-versa. In a negative loop, also known as a balancing loop, a change in one variable induces an opposite behavior in the other variable, i.e., if the value of one of the variable increases then the value of the other variable in the loop would decrease and vice-versa. The system dynamics approach can be divided into four stages [31]. The first stage, qualitative analysis deals with recognizing the problem and identifying the metrics to study the problem. The second stage involves incorporating the identified metrics into a causal loop diagram (CLD). A causal loop diagram illustrates the relationship between the identified metrics or variables. A positive or negative sign is used on the arrow heads connecting the variables. A positive arrow means that a change in the variable at the tail of the arrow induces the same effect on the variable at the arrow head; a negative signs means a change in the variable at the tail of the arrow would induce an opposite effect on the variable at the head of the arrow. The third stage includes simulating the model and the fourth stage involves model testing. The system dynamics approach can be used to model simple linear systems as well as highly non-linear complex systems. This approach has a wide application in economic, ecological and population systems. One of the drawbacks of this model is that users tends to incorporate a lot of variables in the causal loop diagram, thus making it difficult to understand, difficult to metricize and computationally difficult.

According to Zhang et al. [32], any model can be divided into four subsystems or sectors, i.e. project, profit, resource and knowledge sectors. They also say that a project's success depends on its attribution to the strategic development of the enterprise, which can be predicted with the help of a system dynamics model. Due to the ease of applying this model to complex systems, system dynamics is widely used in economic, infrastructure, business processes and population systems where a large number of interdependent variables are used. Causal loop diagrams are constructed to depict the relation between different variables. Alasad et al. [33] emphasize that for any project, the stakeholders are of paramount importance and expert knowledge and perceptions are key requirement to develop a realistic SD model. They provide a well-structured method to incorporate all the knowledge from the stakeholders for development of the stage.

According to Lyneis et al. [34], the highly non-linear nature of feedback systems involved in complex development projects is very difficult to manage using traditional tools such as critical path method (CPM) or program evaluation and review technique (PERT). But system dynamics models significantly improve the quality and performance of management on complex projects. An and Jeng [35] integrate the business process simulation model with the system dynamics approach which helps to evaluate and design the business process so as to optimize the process. They also point out that the business process simulation model can be used to study the deterministic behavior over a short span of time and the system dynamics model can be used to study the evolution of the business over a large time span. Zhu and Wang [36] have developed a system dynamics model which studies the different probable scenarios of economy-environment-resource system to find out the sustainability of the current development mode and substitution rate of technology for natural resources in Jiangxi, China. Such an approach can also be applied to transportation models to relate the economic and non-economic factors and study the overall effect of changes in infrastructure in a dynamic environment.

Sterman et al. [37] describe construction projects as extremely complex systems with multiple independent systems. They also explain that relationships between the sub-systems involved in such projects are highly non-linear and dynamic with multiple feedback processes involved requiring both quantitative and qualitative data. According to Sterman, the system dynamics approach is the best methodology to study such systems. Liu et al. [38] make use of the system dynamics approach to integrate transportation resources and increase the efficiency of capital use to promote economic development of the region [38]. They divide the system dynamics model into four subsystems: social-economic sub-system, demand sub-system, supply sub-system and investment sub-system. The gap between supply and demand is identified as the reason for the structural evolution of transportation corridor. The supply/demand ratio is used to define the demand and supply of various demand nodes. They also identify that the growth in employment opportunities is affected by the degree of urbanization and investment in transportation infrastructure. They suggest that an increase in integrated transportation capacity and an increase in the urbanization ratio would lead to growth of the economy. Su et al. [39] use system dynamics as a supplement to discrete-event simulation to evaluate the unanticipated performance problems within the system of emergency medical services. They use a system dynamics model to account for the feedback effects caused due to human decisions. Also, a lot of complexity is involved while designing a simulation model for emergency response to a disaster and due to this complexity, a system dynamics model was used because of its ability to model complex systems effectively. Sha and Huang [40] study the complexity of the internal structure and operation mechanism of port operation system by developing a generic system dynamics model. They divide the whole subsystem into three subsystems namely time, quality and profit. They try to find effective solutions to solve the issues in a port operation system. Using system dynamics, they are able to study the changes that would occur if a certain factor is changed. They make use of the system dynamics model to guarantee the service time, improve quality time and reduce the cost of port service. Gui et al. [41] develop a system dynamics model to analyze area logistics system. They combine policy decisions with practical operations to provide a thorough understanding of the system mechanism. They emphasize the effectiveness of system dynamics methodology in modeling large complicated systems. They make use of the system dynamics model as this approach uses decision trees with cause and effect relationships that are very effective in analyzing social and economic systems. Sycamore and Collofello [42] integrate system dynamics modeling into a software tool for project management which would help to improve planning and tracking abilities of a project in terms of budget, schedule and rework hours. Here, the system dynamics model analyzes the dependencies among the project variables and the feedback loops that arise due to interdependencies among these variables. They conclude by saying that system dynamics modeling can be used to improve project management activities. Zheng et al. [43] study the interacting relations of aviation logistics and regional economy in Guangxi. These were addressed by CAFTA through developing a system dynamics model. They argue that modern logistics plays an important role in developing a regional economy. A lot of factors, such as influence on infrastructure, foreign trade, regional logistics cost, growth rate of foreign trade, trade with other countries, etc., are involved in describing the relationship between logistics and economy and it is very difficult to explain these interdependencies and the cyclic nature of such factors using traditional methods. They make use of system dynamics to effectively describe the relation between these interacting factors to conclude that investment in aviation logistics and relevant industries is an effective way to promote the development of trade and economy. Zhao et al. [44] uses system dynamics approach to study the relationships between the main factors that influence the formation of logistics hubs. They divide the system into five subsystems namely, industry-policy subsystem, logistics park sub-system, population floating sub-system, logistics supply sub-system and logistics cost sub-system. Using the system dynamics approach, they identify the key factors that form the foundation of promoting regional logistics hubs formation. These works clearly demonstrate the wide application of system dynamics approach and the validity of the approach to address complex transportation infrastructure investment options.

3. LEONTIEF-BASED APPROACH

3.1 MODEL DESCRIPTION

The Leontief input/output model is a quantitative technique that develops a systematic method to study the equilibrium behavior of an economy [9]. In this approach, the system is divided into a number of subsystems and the interdependencies between various subsystems are explained through this model. This method can be used to study the functionality or operability of various subsystems during the changes in some other subsystem. A similar approach can be used for this project where the resources, profit and project could be considered as the various subsystems and their interdependencies can be modeled. As illustrated in equations (3.1)-(3.3) below, the vector Y is the output matrix, or the deliverables, and the vector X represents the input matrix. A is the matrix of multipliers. The multipliers are an indication of if and how the input variables affect the deliverables. The Leontief input-output model can be applied to transport infrastructure projects. The matrix A needs to be determined from historical data using multivariate statistical analysis. Once an estimate for the multipliers is achieved, different sets of input values can be used to calculate the deliverables in each case.

For this project, the following mathematical notation is used,

$$Y = XA + \varepsilon \tag{3.1}$$

Here Y is a 1 by m matrix containing the desired m deliverables/outputs for a project, X is a 1 by (n+1) matrix containing n inputs for the project, A is an (n+1) by m matrix containing the economic multipliers required to calculate the output and ε is the vector of error. In X, a one in the first column is a multiplier of a constant term that would be used later to fit the model. Hence, an artificial variable $X_{0i} = 1$ has to be added.

Applying the above equation to the metrics of the project we get the equation,

$$[Y_1 \quad Y_2 \quad Y_3 \quad Y_4 \quad Y_5 \quad Y_6 \quad Y_7 \quad Y_8 \quad Y_9 \quad Y_{10} \quad Y_{11}] = [1 \quad X_{11} \quad X_{12}] * \begin{bmatrix} A_{01} & A_{02} & A_{03} & A_{04} & A_{05} & A_{06} & A_{07} & A_{08} & A_{09} & A_{010} & A_{011} \\ A_{11} & A_{12} & A_{13} & A_{14} & A_{15} & A_{16} & A_{17} & A_{18} & A_{19} & A_{110} & A_{111} \\ A_{21} & A_{22} & A_{23} & A_{24} & A_{25} & A_{26} & A_{27} & A_{28} & A_{29} & A_{210} & A_{211} \end{bmatrix} + [\mathcal{E}_1 \quad \mathcal{E}_2 \quad \mathcal{E}_3 \quad \mathcal{E}_4 \quad \mathcal{E}_5 \quad \mathcal{E}_6 \quad \mathcal{E}_7 \quad \mathcal{E}_8 \quad \mathcal{E}_9 \quad \mathcal{E}_{10} \quad \mathcal{E}_{11}] \qquad (3.2)$$

Variables used in equation (3.2) are mentioned in Table 3.1.

Table 3.1 Variables Used in Equation (3.2)

Matrix Y	Matrix A			Matrix X
Y_1 -Number of Jobs Created	A_{01} - number of jobs created due to other factors	A_{11} - number of jobs created per $ invested	A_{21} - number of jobs created per person hired	X_1 – Amount of Money invested
Y_2 - Increase in Tax Revenue ($)	A_{02} - increase in tax revenue due to other factors	A_{12} - increase in tax revenue per $ invested	A_{22} - increase in tax revenue per person hired	
Y_3 - Increase in Local Business Revenue ($)	A_{03} - increase in local business revenue due to other factors	A_{13} - increase in local business revenue per $ invested	A_{23} - increase in local business revenue per person hired	
Y_4 - Increase in Utility Revenue ($)	A_{04} - increase in utilities revenue due to other factors	A_{14} - increase in utilities revenue per $ invested	A_{24} - increase in utilities revenue per person hired	
Y_5 - Decrease in Passenger’s Travel Time (minutes/passenger)	A_{05} - decrease in travel time due to other factors	A_{15} - decrease in travel time per $ invested	A_{25} - decrease in travel time per person hired	
Y_6 - Decrease in Travel Cost for the Passengers ($/passenger)	A_{06} - decrease in travel cost due to other factors	A_{16} - decrease in travel cost per $ invested	A_{26} - decrease in travel cost per person hired	X_2 – Number of workers hired
Y_7 - Decrease in Costs Accumulated by Shippers ($)	A_{07} - decrease in costs accumulated by shippers due to other factors	A_{17} - decrease in costs accumulated by shippers per $ invested	A_{27} - decrease in costs accumulated by shippers per person hired	
Y_8 - Decrease in Costs Accumulated by Receivers ($)	A_{08} - decrease in costs accumulated by receivers due to other factors	A_{18} - decrease in costs accumulated by receivers per $ invested	A_{28} - decrease in costs accumulated by receivers per person hired	
Y_9 – Increase in corridor capacity (%)	A_{09} – increase in corridor capacity due to other factors	A_{19} – increase in corridor capacity per $ invested	A_{29} - increase in corridor capacity per person hired	
Y_{10} – Increase in level of service (%)	A_{010} – increase in level of service due to other factors	A_{110} - increase in level of service per $ invested	A_{210} - increase in level of service per person hired	
Y_{11} – Increase in Accessibility (%)	A_{011} – increase in accessibility due to other factors	A_{111} - increase in accessibility per $ invested	A_{211} - increase in accessibility per person hired	

3.2 MODEL FITTING

To fit the model, historical data for X and Y are required from similar projects. Using these data we can calculate the values of elements of matrix A.

For instance as shown in Table 3.2, from the historical data of k similar projects, information about the output and input variables in equation (3.1) is available.

Table 3.2 Data for Fitting Leontief Model

Project ID	Independent Variables (Inputs), X						Dependent Variables (Outputs), Y					
	X_1	X_2	…	X_j	…	X_n	Y_1	Y_2	…	Y_i	…	Y_m
1												
2												
…												
p				X_j^p						Y_i^p		
…												
k												

For k projects, equation (3.2) can be written as:

$$\begin{bmatrix} Y_{11} & \cdots & Y_{1m} \\ \vdots & \ddots & \vdots \\ Y_{k1} & \cdots & Y_{km} \end{bmatrix} = \begin{bmatrix} 1X_{11} & \cdots & X_{1n} \\ \vdots\ \vdots & \ddots & \vdots \\ 1X_{k1} & \cdots & X_{kn} \end{bmatrix} * A + \begin{bmatrix} \varepsilon_{11} & \cdots & \varepsilon_{1m} \\ \vdots & \ddots & \vdots \\ \varepsilon_{k1} & \cdots & \varepsilon_{km} \end{bmatrix} \tag{3.3}$$

Here, Y_{11} is the number of jobs created from the first project and Y_{k1} is the number of jobs created from the k^{th} project. Similarly, X_{11} is the amount of money invested in the first project and X_{k1} is the amount of money invested in k^{th} project.

Equation (2.3) is a multivariate regression model and can be rewritten as:

$$Y_{(k\times m)} = X_{(k\times(n+1))}\,A_{((n+1)\times m)} + \mathcal{E}_{(k\times m)} \tag{3.4}$$

The above regression model has the following assumptions:

(1) $E(\mathcal{E}_i) = 0$, and (2) $Cov(\mathcal{E}_p, \mathcal{E}_q) = \sigma_{pq}I$ for all p,q =1, 2,…, m

Since the values for Y and X are available, A can be calculated as follows:

$$A_{(i)} = (X'X)^{-1}X'Y_{(i)} \tag{3.5}$$

The value of the multipliers, i.e. A can also be calculated using statistical software such as SAS. These multipliers can be used to fit the model. After fitting the model, goodness of fit, r^2, can be calculated to see how well the model fits. This can also be done using the statistical software SAS.

3.3 NUMERICAL EXAMPLE

Assume that historical data was collected from 10 similar projects as shown in Table 3.3. Variables are defined in Table 3.1.

Table 3.3 Data for the Numerical Example

S. No.	INPUTS		OUPUTS										
	X_1	X_2	Y_1	Y_2	Y_3	Y_4	Y_5	Y_6	Y_7	Y_8	Y_9	Y_{10}	Y_{11}
1	10,000,000	40	46	200,000	800,000	20,000	30	20	15,000	17,000	0.16	0.20	0.10
2	15,000,000	48	54	270,000	1,200,000	30,000	45	30	22,000	24,000	0.24	0.30	0.15
3	5,000,000	24	31	70,000	400,000	10,000	15	10	6,000	8,000	0.08	0.10	0.05
4	8,000,000	30	37	85,000	650,000	16,000	24	16	9,000	11,000	0.10	0.16	0.08
5	3,000,000	14	19	50,000	250,000	6,000	8	6	2,000	4,000	0.03	0.06	0.03
6	22,000,000	60	74	500,000	1,800,000	44,000	65	44	37,000	41,000	0.35	0.44	0.22
7	17,000,000	55	63	350,000	1,400,000	34,000	53	35	33,000	36,000	0.29	0.34	0.17
8	12,000,000	44	52	250,000	1,000,000	24,000	36	25	18,000	23,000	0.19	0.24	0.12
9	9,000,000	35	42	180,000	750,000	18,000	27	18	12,000	15,000	0.13	0.18	0.09
10	6,000,000	28	34	77,000	500,000	13,000	18	14	8,000	10,000	0.11	0.12	0.06

Using SAS (Appendix A), the model was fitted and the results were obtained as shown in Table 3.4.

Table 3.4 Model Fitting Results (Matrix A)

A01 = 6.982274447	A11= 0.000000934	A21= 0.746586559
A02 = -6845.913829	A12= 0.017725	A22= 930.941896
A03 = -1268.007701	A13= 0.081066	A23= 234.385949
A04 = 63.40038505	A14= 0.00194669	A24= 16.05848031
A05 = -2.372634933	A15= 0.000002630	A25= 0.167629290
A06 = -.6845913829	A16= 0.0000017725	A26= 0.0930941896
A07 = -6187.213702	A17= 0.001587	A27= 143.098984
A08 = -5024.297949	A18= 0.001595	A28= 181.338379
A09 = -.0378311093	A19 = 0.0000000119	A29 = 0.0020874549
A010 = -8.04912E-16	A110 = 2E-8	A210 = 6.134247E-17
A011 = -4.02456E-16	A111 = 1E-8	A211 = 3.067123E-17

This fitted model can now be applied in equation 3.2. To check the goodness of fit of the model, the value of R-square for the model can be seen in the SAS results. Now, this fitted model can be used to find the output of the model.

Suppose the inputs are as follows:

Amount of money invested = $28 million

Manpower hired = 235 people

Substituting the values of input in the fitted model, output is calculated as shown in Table 3.5.

Table 3.5 Outputs for the Numerical Example

Y_1 -Number of Jobs Created	209
Y_2 - Increase in Tax Revenue ($)	708225.43
Y_3 - Increase in Local Business Revenue ($)	2323660.7
Y_4 - Increase in Utility Revenue ($)	58344.463
Y_5 - Decrease in Passenger's Travel Time (minutes/passenger)	110.66025
Y_6 - Decrease in Travel Cost for the Passengers ($/passenger)	70.822543
Y_7 - Decrease in Costs Accumulated by Shippers ($)	71877.048
Y_8 - Decrease in Costs Accumulated by Receivers ($)	82250.221
Y_9 – Increase in corridor capacity (%)	79%
Y_{10} – Increase in Level of Service (%)	56%
Y_{11} – Increase in Accessibility (%)	28%

4. BAYESIAN APPROACH

4.1 MODEL DESCRIPTION

The Bayesian network model is a graphical method that makes use of probability to establish decision criteria. This approach helps to express the range of likelihood of outcomes and also as the investment process unfolds, improved estimates can be made. This is a characteristic of the Bayesian networks as revised estimates can be made additional data appear. Thus, as more information becomes available decision-makers could make adjustments in their decisions. It can also help to study the extent to which a particular critical infrastructure could be affected through various factors and the effect on other critical infrastructures [25]. It helps to study three major aspects [25]:

- Reliability analysis – Helps to calculate the probability that a particular critical infrastructure will operate for a certain period of time without failure
- Adverse events propagation – Helps to evaluate the effect of adverse events on critical infrastructures. It also aims to control the situation and prevent further degradation
- Diagnosis – It helps establishing a relationship between the failure of a specific critical infrastructure, its causes and its consequences

A similar approach can be used for this project to study the interdependencies by considering the metrics as various variables or nodes. The relationship between decision variables, evaluation criteria and the objective variables are depicted in the Bayesian network diagram (Figure 4.1).

The first step in this approach is to create a Bayesian Network. The variables selected in a Bayesian Network are mapped according to a certain criteria. Normally, there are three types of variables that are used to form a Bayesian Network. These are the decision items, evaluation criteria and the objective functions [15].

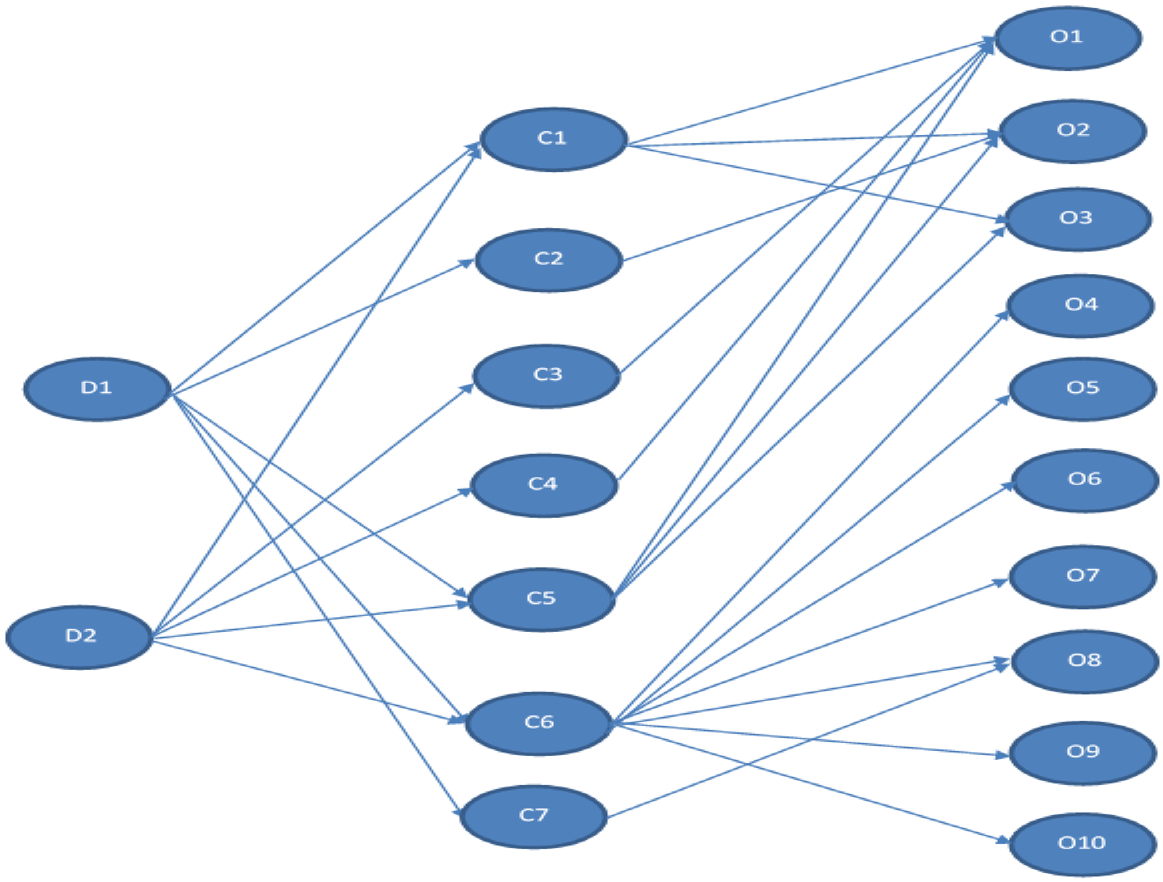


Figure 4.1 Bayesian Network

Decision items are the variables, mainly the inputs, on which a decision has to be taken, evaluation criteria are those variables that help to evaluate the decisions taken, and finally, the objective function consists of the variables that are the outputs or the expected deliverables from the project. Decision variables, evaluation criteria and objective variables are shown in the tables below. Evaluation criteria are the missing link between the decision variables and the objective functions. It is a way of analyzing the extent to which the decision variables are able to fulfill the desired objective functions. State policy regarding infrastructure can influence the amount of money being invested in a project. Favorable state and tax policies can encourage investment and give stakeholders more confidence in the project, thereby improving the chances of getting close to the acceptable/favorable values of the objective functions. Employment policy, population density and degree of urbanization play an important role in deciding the amount of money to be invested and the manpower hired. For instance, if the employment policy is favorable and if investing in infrastructure would lead to job creation, then the organization would be more inclined to invest in the region. The evaluation criteria, service requirement and accessibility are two factors that would help the investors to evaluate the outputs for their project as to realize the profit from the project, service quality and accessibility need to be improved. The variables such as tax revenue generated and increase in local business revenue can be reclassified as satisfaction to the government sector. Decrease in shippers' and receivers' cost may be attributed to the satisfaction of the private sector and jobs created can be related to the satisfaction of the public sector. In figure 1 the arrow from D1 to C1 depicts the conditional probability (CPT) between the decision item d_1 and evaluation criteria c_1. The CPT relationship between each pair of connected nodes is expressed in the form of a probability distribution that contains the statistical information of the decision makers' experience [15]. The equations to calculate these conditional probabilities are given in equations (4.1) to (4.4), below. Finally, a concluding decision can be made based on the optimum expected values of the objective variables [45]. Here, it is worth mentioning that the decision network varies according to the characteristics and requirements of each project and the associated objectives, and an expert panel and the decision network must be chosen accordingly [45].

The decision variables, evaluation criteria and objective variables are shown in the Tables 4.1, 4.2 and 4.3, respectively.

Table 4.1 Decision Variables

Node	Decision Variable	Decision State
D1	$ amount invested	Low: <0.5 millions Moderate: 0.5~5millions High: >5 millions
D2	# workers hired	Low: <50 Moderate: 50 to 150 High: >150

Table 4.2 Evaluation Criteria

Node	Evaluation Criteria	Alternate States
C1	State policy regarding infrastructure investment	Favorable Unfavorable
C2	Tax policy	Favorable Unfavorable
C3	Employment policy	Favorable Unfavorable
C4	Population Density	Low Moderate High
C5	Degree of Urbanization	Low High
C6	Service Requirement	Low Moderate High
C7	Accessibility	Low Moderate High

Table 4.3 Objective Variables

Node	Objective Variables	Alternate States
O1	#job created	Low Moderate High
O2	tax revenue generated	Low Moderate High
O3	Increase in utility revenue	Low Moderate High
O4	Decrease in passenger's travel time	Low High
O5	Decrease in shippers' cost	Low Moderate High
O6	Decrease in receivers' cost	Low Moderate High
O7	Local business revenue generated	Low Moderate High
O8	Decrease in travelling cost for passengers	Low Moderate High
O9	Level of Service	Low Moderate High
O10	Corridor Capacity	Low Moderate High

The next step is to decide on the alternate states for the decision items. These states need to be defined after completing expert surveys. For example, alternate states for the decision variables are shown in Table 4.4.

Table 4.4 Alternate States for Decision Items*

Decision item	Alternate states
1. Amount of money invested (node D1)	Low: < $500,000 Moderate: $500,000 to $5,000,000 High: >$5,000,000
2. Number of workers hired (node D2)	Low: <50 Moderate: 50 to 150 High: >150

*The above values are arbitrary and are used just to provide an example. The value of the alternate states will differ from one organization to another.

Similarly, alternate states are set for the evaluation criteria and objective functions as well. A score is given to each state of the objective variable, as shown in Table 4.5.

Table 4.5 Alternate States of Objective Variable Number of Jobs Created**

Objective variable	Alternate states	Score
Number of jobs created (node O1)	High: >300	10
	Moderate: 20-300	5
	Low:<20	1

**The values shown in table 11 are arbitrary and are used as an example. The value of the alternate states and the scores has to be decided after conducting an expert survey.

Conditional probability tables (CPT) can similarly be created for each pair of nodes.

Using the CPT, probability for a node X_o at a value x_o can be calculated as shown in equation 4.1.

$$\Pr(x_0|x_p) = 1 - \prod_{i:Xi \in Xp} (1 - p_i) \tag{4.1}$$

Where X_p are the parent nodes of node X_o, and p_i is the probability that X_o is true given that all the cause subset X_p is present.

For example to calculate the conditional probability for node C1, for a given set of values for the input variables, D1 and D2, equation 4.1 can be used as:

$$Pr(C_1=c_1|D_1=d_1; D_2=d_2) = 1-\{1-Pr(C_1=c_1| D_1=d_1)\}* \{1-Pr(C_1=c_1| D_2=d_2)\} \quad (4.2)$$

Similarly, equation 4.1 can be used to calculate the conditional probabilities for the evaluation criteria variables and the objective variables. Once all the probabilities are calculated, the expected value of the objective function can be calculated. For example, for O_2 the objective value of the function can be calculated using the equation (4.3) and (4.4).

$$Pr(O_2=o_2)=\sum_{c_1}\sum_{c_2} Pr(O_2 = o_2|C_1 = c_1; C_2 = c_2) \quad (4.3)$$

$$E(O_2) = \sum_{o_2} o_2 Pr(O_2) \quad (4.4)$$

The above procedure can be repeated to find the expected value of all the objective variables.

After calculating the objective values for different sets of values for the input variables, D1 and D2, solutions can be compared with each other to arrive at the best non-inferior solution.

4.2 MODEL FITTING

Once the alternate states for all the variables are defined, a conditional probability table, based on the expert poll, needs to be formulated for each pair of nodes. The survey/poll must be held among experts from all the stakeholder groups. For example, to assign conditional probabilities for the amount of money invested, node D1, and the state policy regarding investment in infrastructure and tax policy, node O1, a survey needs to be conducted and the experts should be asked for their opinions. The survey results from one such expert are as depicted in Table 4.6.

Table 4.6 Rating of a Decision Item under a Criterion

Decision Item	Evaluation criteria	
Amount of money to be invested (node D1)	State tax policy (node C1)	
	Unfavorable	Favorable
Low: < $500,000	x	
Moderate: $500,000 to $5,000,000		x
High: >$5,000,000		x

Once the opinion from the entire panel of experts is gathered, a conditional probability table is formulated. Table 4.7 shows an example of conditional probability table.

Table 4.7 Conditional Probability Table from Node D1 to C1

Decision Item	Evaluation criteria	
Amount of money to be invested (node D1)	State tax policy (node C1)	
	Unfavorable	Favorable
Low: < $500,000	0.6	0.4
Moderate: $500,000 to $5,000,000	0.3	0.7
High: >$5,000,000	0	1

Table 4.7 shows that 60% people would invest a low amount if the tax policy is unfavorable and 40% people would invest a low amount of money only if the tax policy

is favorable. For a moderate investment amount, 70% will invest only if the tax policies are favorable and only 30% would invest even if the tax policy is unfavorable and so on.

4.3 NUMERICAL EXAMPLE

Consider an example with two decision items, two evaluation criteria and two objective variables. Here the decision items are the amount of money invested and manpower hired. The variables for evaluation criteria are service quality and degree of urbanization, and the variables for objective function are number of jobs created and increase in tax revenue.

The amount of money that should be invested (node D1) can be evaluated based on the factors service requirement (node C1) and degree of urbanization (node C2). The number of workers to be hired (node D2) can be evaluated by the factor degree of urbanization (node C2). Further, depending upon the service requirement (node C1) achieved jobs (node O1) would be created and the tax revenue would increase (node O2). Also, degree of urbanization (node C2) would further have an impact on the number of jobs created (node O1). The above information is represented through a Bayesian network diagram.

The decision variables, evaluation criteria and objective variables with their respective alternate states are described in Tables 4.8, 4.9 and 4.10, respectively.

Table 4.8 Decision Items

Decision items	Alternate states
1. Amount of money invested (Node D1)	Low: < $500,000 Moderate: $500,000 - $5,000,000 High: >$5,000,000
2. Manpower hired (Node D2)	Low: <50 Moderate: 50 to 150 High: >150

Table 4.9 Evaluation Criteria

Evaluation criteria	Alternate states
1. Service Requirement (Node C1)	Low Moderate High
2. Degree of urbanization (Node C2)	Low High

Table 4.10 Objective Variables

Objective variable	Alternate states
1. Number of jobs created (Node O1)	Low: <50 Moderate : 50-250 High: >250
2. Increase in tax revenue (Node O2)	Low Moderate High

Figure 4.2 represents the Bayesian network for the numerical example described above. The arrows represent the interconnectedness between the various variables.

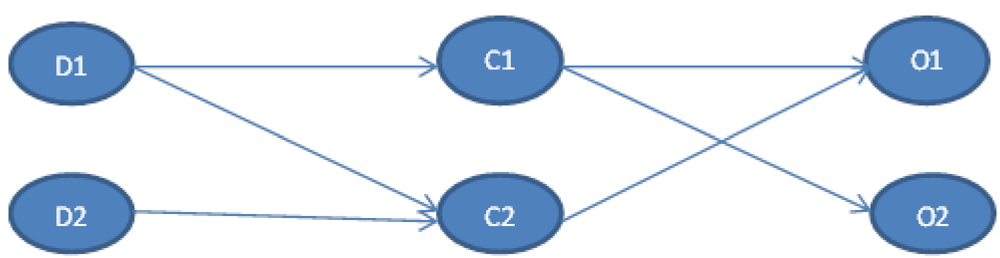


Figure 4.2 Bayesian Network for the Numerical

After analyzing the alternate states for the variables, an expert survey has to be done to form the conditional probability tables (CPT). Suppose after conducting the survey and obtaining the results, CPT Tables 4.11, 4.12, 4.13, 4.14, 4.15 and 4.16 were obtained.

Table 4.11 CPT for Amount of Money Invested and Service Requirement

Amount of Money Invested (node D1)	Service Requirement (node C1)		
	Low	Moderate	High
Low: < $500,000	0.9	0.1	0
Moderate: $500,000-$5,000,000	0.1	0.6	0.3
High: >$5,000,000	0	0.3	0.7

Table 4.12 CPT for Amount of Money Invested and Effect on Degree of Urbanization

Amount of Money Invested (node D1)	Degree of Urbanization (node C2)	
	Low	High
Low: < $500,000	0.9	0.1
Moderate: $500,000-$5,000,000	0.6	0.4
High: >$5,000,000	0.2	0.8

Table 4.13 CPT for Manpower Hired and Degree of Urbanization

Manpower Hired (node D2)	Degree of Urbanization (node C2)	
	Low	High
Low: < $500,000	0.9	0.1
Moderate: $500,000-$5,000,000	0.6	0.4
High: >$5,000,000	0.2	0.8

Table 4.14 CPT for Service Requirement and Jobs Created

Service Requirement (node C1)	Number of Jobs Created (node O1)		
	Low: <50	Moderate: 50-250	High: >250
Low	0.9	0.1	0
Moderate	0.2	0.6	0.2
High	0.1	0.1	0.8

Table 4.15 CPT for Service Requirement and Increase in Tax Revenue

Service Requirement (node C1)	Increase in Tax Revenue (node O2)		
	Low	Moderate	High
Low	0.9	0.1	0
Moderate	0.1	0.6	0.3
High	0.1	0.7	0.2

Table 4.16 CPT for Degree of Urbanization and Number of Jobs Created

Degree of Urbanization (node C2)	Number of Jobs Created (node O1)		
	Low: <50	Moderate: 50-250	High: >250
Low	0.8	0.2	0
High	0.1	0.3	0.6

Using the conditional probabilities, probability for each variable depending on the states of the preceding variables can be calculated using the following formula:

$$\Pr(x_0|x_p) = 1 - \prod_{i:Xi \in Xp} (1 - p_i) \tag{4.5}$$

Using the above formula, the probabilities are obtained as shown in the Tables 4.17 and 4.18. Probability for the variable service quality (node C1) and increase in tax revenue (node O2) would be the same as their respective conditional probability tables as they have a single parent node.

Table 4.17 Probability for Degree of Urbanization for All Sets of Decision Items

Decision Items		Degree of Urbanization (node C2)	
Amount of Money Invested (node D1)	Manpower Hired (node D2)	Low	High
Low	Low	0.99	0.19
Low	Moderate	0.96	0.46
Low	High	0.92	0.82
Moderate	Low	0.96	0.46
Moderate	Moderate	0.84	0.64
Moderate	High	0.68	0.88
High	Low	0.92	0.82
High	Moderate	0.68	0.88
High	High	0.36	0.96

Table 4.18 Probability for Number of Jobs Created for All Sets of Evaluation Criteria Variables

Evaluation Criteria		Number of Jobs Created node (O1)		
Service Requirement (node C1)	Degree of Urbanization (node C2)	Low: <50	Moderate: 50-250	High: >250
Low	Low	0.98	0.28	0
Low	High	0.91	0.37	0.6
Moderate	Low	0.84	0.68	0.2
Moderate	High	0.28	0.72	0.68
High	Low	0.82	0.28	0.8
High	High	0.19	0.37	0.92

Now, a rating scale is decided for the alternate states of the objective variables. Rating should be done by experts. The ratings for the alternate states of the objective function can be found in Table 4.19.

Table 4.19 Rating Scale for the Objective Variables

Objective variable	Alternate states	Rating Scale
1. Number of jobs created (node O1)	Low	1
	Moderate	5
	High	9
2. Increase in Tax Revenue (node O2)	Low	1
	Moderate	5
	High	9

After deciding the rating scales and calculating the combined probabilities for all decision states, the expected value for the objective function is calculated for each decision state. For instance, the expected value of the objective variable is calculated for the decision states when the inputs are moderate amount of money invested and a high number of manpower hired. The expected value for the objective variables is calculated using equation (4.4).

E(Number of Jobs created) = Rating*Pr(Low Jobs Created) + Rating* Pr(Moderate Jobs Created) + Rating*(High Jobs Created)

Using the values from the conditional probability tables and the combined probability tables, the probabilities for each scenario can be found.

Pr(Low Jobs Created) = (0.98*0.68*0.1) + (0.91*0.88*0.1)+ (0.84*0.68*0.6) + (0.28*0.88*0.6)+ (0.82*0.68*0.3) + (0.19*0.88*0.3) = 0.855

Pr(Moderate Jobs Created) = (0.28*0.68*0.1) + (0.37*0.88*0.1)+ (0.68*0.68*0.6) + (0.72*0.88*0.6)+ (0.28*0.68*0.3) + (0.37*0.88*0.3) = 0.864

Pr(High Jobs Created) = (0.0*0.68*0.1) + (0.6*0.88*0.1)+ (0.2*0.68*0.6) + (0.68*0.88*0.6)+ (0.8*0.68*0.3) + (0.92*0.88*0.3) = 0.899

Hence, E(Number of Jobs Created) = 1*0.855 + 5*0.864 + 9*0.899 = 13.270

E(Increase in Tax Revenue) = Rating*Pr(Low Increase in Tax Revenue) + Rating* Pr(Moderate Increase in Tax Revenue) + Rating*(High Increase in Tax Revenue)

Pr(Low Increase in Tax Revenue) = (0.9*0.1) + (0.1*0.6) + (0.1*0.3) = 0.18

Pr(Moderate Increase in Tax Revenue) = (0.1*0.1) + (0.6*0.6) + (0.7*0.3) = 0.58

Pr(High Increase in Tax Revenue) = (0*0.1) + (0.3*0.6) + (0.2*0.3) = 0.24

Hence, E(Increase in Tax Revenue) = 1*0.18 + 5*0.58 + 9*0.24 = 5.24

So for the set of input, moderate amount of money invested and high manpower hired expected values for the objective variables are found as shown in the Table 4.20.

Table 4.20 Numerical Results - Bayesian Approach

	Inputs		Expected value for the objective function	
	Amount of Money Invested (node D1)	Manpower Hired (node D2)	Number of Jobs Created (node O1)	Increase in Tax Revenue (node O2)
Alternate State	Moderate	High	13.270	5.24

Similarly, the expected value of objective function can be calculated for each alternate state of the decision set. Based upon the expected values of the objective variables, a criterion is set by the experts and the best non-inferior solution is selected.

5 SYSTEM DYNAMICS APPROACH

5.1 MODEL DESCRIPTION

The system dynamics approach can be used to identify the major factors impacting project performance. According to this methodology, any system can be divided into four subsystems i.e. project, resources, profit and knowledge [36]. The subsystem- profit can be quantified using factors such as number of jobs created, increased revenues, etc. as metrics. To quantify resources, metrics such as investment amount, manpower and raw material required can be used. The last subsystem, i.e., knowledge, can be divided into implicit and tacit knowledge. The modeling process using the above approach can be divided into two parts, i.e., Qualitative System Dynamics and Quantitative System Dynamics [46]. The qualitative part, also known as model conceptualization, includes identifying the critical factors (metrics in this case), developing a framework of the model and finally creating Causal Loop Diagrams (CLD). After successfully identifying the metrics to be used in the model, a CLD was developed (Figure 3). The arrows specify the relation between variables, i.e., a change in the variable at the tail of the arrow will bring about a change in the variable at the arrow head. The positive sign on the head of the arrow specifies that an increase in value of the variable at the tail of the arrow will cause an increase in the value of the variable at the arrowhead and vice-versa. A negative sign specifies that an increase in the value of the variable at the tail of the arrow will decrease the value of the variable at the arrowhead and vice-versa. A unique feature about the causal loop diagram is that it involves feedback loops. The feedback loops can be either positive loops or negative loops. A positive feedback loop, also known as a reinforcing loop, is the one in which a change in the quantity of a variable induces a similar change in the value of the other variable included in the loop. A negative feedback loop, also known as a balancing loop, is the one in which a change in the quantity of a variable induces a an opposite change in the value of the other variable included in the loop.

The causal loop diagram (CLD) in Figure 5.1 was made using the Vensim PLE software. The CLD shows that an increase in manpower hired would cause an increase in the number of jobs created, local business revenue, network efficiency, accessibility, service level and a decrease in the travel time. Also, increasing the manpower would cause a decrease in the costs accumulated by the shippers and the receivers. Investing more money would in turn increase the number of jobs, local business revenue, network efficiency, accessibility, service level, corridor capacity and a decrease in travel time and the shippers and receivers cost. An increase in the number of jobs would increase utility revenue and tax revenue. If utility revenue increases, this would lead to an increase in the tax revenue and local economic growth. An increase in the local business revenue would lead to an increase in the tax revenue and would also lead to local economic growth. More rail revenue would be generated if network efficiency, accessibility, service level, corridor capacity are increased and travel time and costs associated with shipping and receiving are reduced. Tax revenue would also be increased due to an increase in the rail revenue. Tax revenue and local economic growth form a reinforcing loop which means that an increase in tax revenue would lead to local economic growth and, local economic growth would lead to an increase in the tax revenue and so on. Local economic growth would attract more investments in the region and would generate new business opportunities that would further help in local economic growth. Local economic growth and national economic growth also form a reinforcing loop i.e. local economic growth would lead to national economic growth and national economic growth would in turn lead to local economic growth and so on. Depending on the type of the project and the variables involved, it might be the case that local economic growth does not lead to national economic growth and vice-versa, therefore, in such a case the multipliers/parameters that relate local and national economic growth may equal to zero. Figure 5.1 shows a causal loop diagram.

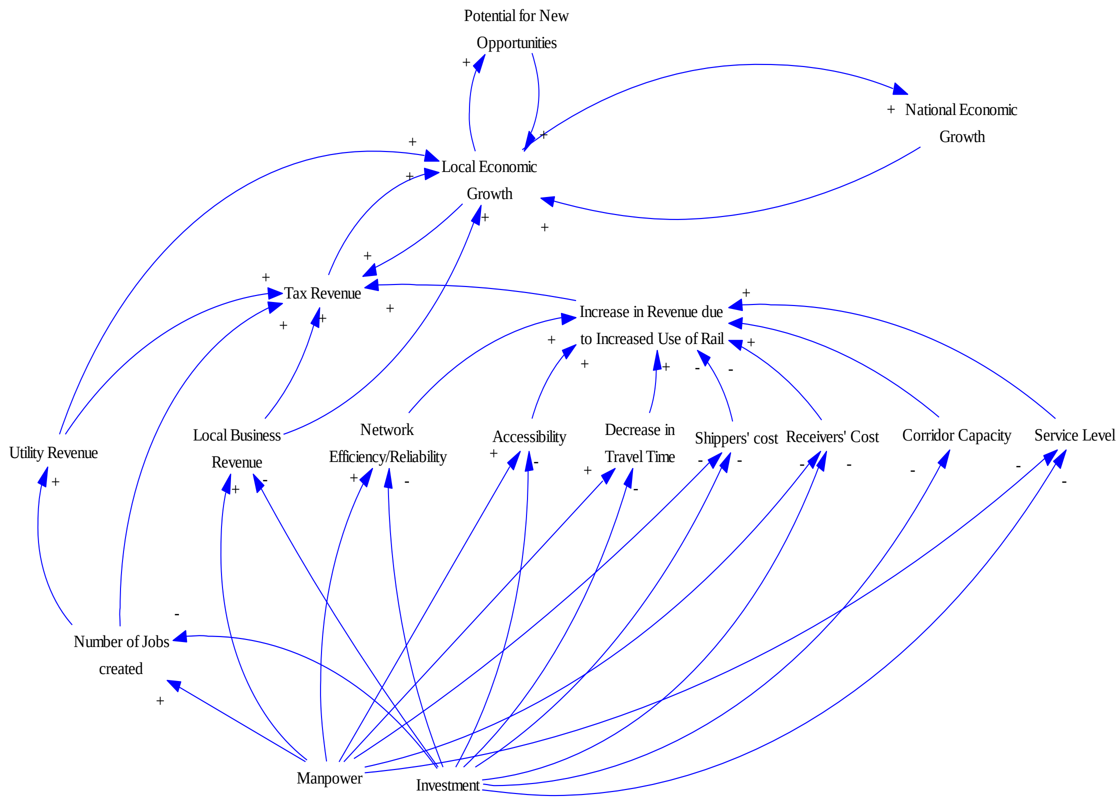


Figure 5.1 Causal Loop Diagram

After understanding the relation between various variables and putting those into a causal loop diagram, economic multipliers or parameter estimates are needed. These economic multipliers define the relation between two variables. Estimating the parameters is a controversial area and not easily accomplished. Extra care must be taken while estimating the parameters as experts might not agree with the parameters estimated using regression analysis or other techniques. The parameters must be estimated by incorporating the experts' opinions along with the historical data. The multipliers for this project are described in Table 5.1.

Table 5.1 Variables and Multipliers Used in the System Dynamics Approach

Relation Between	**Parameter estimates**
Money invested & Jobs created	Jobs created per $ invested (X1)
Manpower hired & Jobs created	Jobs created per person hired (X2)
Money invested &Local Business Revenue	Increase in local business revenue per $ invested (X3)
Manpower hired & Local Business Revenue	Increase in local business revenue per person hired (X4)
Money invested & Utility Revenue	Increase in utilities revenue per $ invested (X5)
Manpower hired & Utility Revenue	Increase in utilities revenue per person hired (X6)
Money invested & Network Efficiency	Increase in network efficiency per $ invested (X7)
Manpower hired & Network Efficiency	Increase in network efficiency per person hired (X8)
Money invested & Accessibility	Increase in accessibility per $ invested (X9)
Manpower hired & Accessibility	Increase in accessibility per person hired (X10)
Money invested & Decrease in Travel time	Decrease in Travel time per $ invested (X11)
Manpower hired & Decrease in Travel time	Decrease in Travel time per person hired (X12)
Money invested & Decrease in Shipping cost	Decrease in Shipping cost per $ invested (X13)
Manpower hired & Decrease in Shipping cost	Decrease in Shipping cost per person hired (X14)
Money invested & Decrease in Receiving cost	Decrease in Receiving cost per $ invested (X15)
Manpower hired & Decrease in Receiving cost	Decrease in Receivers' cost per person hired (X16)
Rail revenue & Network Efficiency	Increase in Rail revenue per % increase in Network Efficiency (X17)
Rail revenue & Accessibility	Increase in Rail revenue per % increase in Accessibility (X18)
Rail revenue & Decrease in Shipping Cost	Increase In Rail Revenue per $ decrease in Shipping cost (X19)
Rail revenue & Decrease in Receiving Cost	Increase In Rail Revenue per $ decrease in Receiving cost (X20)
Rail revenue & Decrease in Travel time	Increase in Rail revenue due to % decrease in travel time (X21)
Tax Revenue & Utility Revenue	Increase in Tax Revenue per $ increase in Utility Revenue (X22)
Tax Revenue & Local Business Revenue	Increase in Tax Revenue per $ increase in Local Business Revenue (X23)
Tax Revenue & Rail Revenue	Increase in Tax Revenue per $ increase in Rail Revenue (X24)
Local Economic Growth & Tax Revenue	Local Economic Growth per $ increase in Tax Revenue (X25)
Local Economic Growth & Local Business revenue	Local Economic Growth per $ increase in Local Business Revenue (X26)
Local Economic Growth & Rail Revenue	Local Economic Growth per $ increase in Rail Revenue (X27)
Local Economic Growth & Utility Revenue	Local Economic Growth per $ increase in Utility Revenue (X28)
New opportunities & Local Economy	New Opportunities per $ increase in Local Economy (X29)
National economy & Local Economy	National Economic Growth per $ Local Economic Growth (X30)
Money Invested & Corridor Capacity	Percentage increase in Corridor Capacity per $ invested (X31)
Money Invested & Service level	Percentage Increase in Service Level per $ invested (X32)
Manpower hired & Service Level	Percentage Increase in Service Level per person hired (X33)

5.2 MODEL FITTING

To estimate the parameters, data must be used from below the level of aggregation of the model, i.e. from expert surveys and interviews, engineering data and other sources which gives a descriptive knowledge of the model rather than using the historical data that explains the aggregate behavior of the model [47]. As mentioned above, it is very important to incorporate expert's opinions along with the historical data for parameter estimation. To define the parameters for some of the variables, it might be of best interest that experts estimate it based on their judgment and experience as historical data might yield some results that are not correct for the model. Also, the parameters estimated from historical data may not be valid for the project in hand depending upon the lifespan of the project, technological changes, etc. Therefore, a panel of experts must be set-up and results from surveys and interviews must be collected along with the historical data in order to get the right estimates. Once the parameters are estimated and the model is fitted, the goodness of fit of the model is calculated. The fitted model is now simulated over time beyond the period of fit. For good parameter estimation, historical time-series data for the involved elements are required. These are important as system dynamics models are capable of predicting how the variables change over a period of time. The time period for which the data need to be collected depends upon the nature of the project and also on the nature of the variables involved.

Since this is a time-series model, parameter estimation can be done by using regression on fixed x's and lagged y's [34].

$$y_t + \alpha_1 y_{t-1} + \cdots + \alpha_p y_{t-p} = \beta_1 x_{1t} + \cdots + \beta_q x_{qt} + \mathcal{E}_t \quad (t = 1, \ldots., n) \quad (5.1)$$

Where y_t is the output at time t, $\{x_{1t}\}$,…., $\{x_{qt}\}$ are the sequences of constants (inputs in this case), $\mathcal{E}_t$ is the error term at time t, p is the time. Putting $y_{t-1} = x_{q+i,t}$ and $\alpha_i = -\beta_{q+I}$ (i=1,….,p) in equation (6.1), the model can be written as:

$$y_t = \beta_1 x_{1t} + \cdots + \beta_{q+p} x_{q+p,t} + \mathcal{E}_t \;\; (t = 1, \ldots, n) \quad (5.2)$$

Equation (6.2) can be written in matrix notation as:

$$y = X\beta + \mathcal{E} \quad (5.3)$$

For every single dependent variable, linear regression can now be done to estimate the relationship between each set of a single dependent variable and one or more independent variables. For example, from the causal loop diagram (Figure 5.1), variable local business revenue is dependent upon investment and manpower. In equation (5.1), investment and manpower can act as inputs x_1 and x_2 respectively, and the variable local business revenue can act as an output, y_1, for these inputs. Now, x_1 and x_2 are constants and variable $y_1$changes with time. Hence information for y_1 would be needed over a period of time. Table 5.2 shows the format in which data would be required. Thus, historical data for X and Y are required from similar projects. Using these data we can estimate the parameters β.

Table 5.2 Data for Fitting System Dynamics Model

Project ID	Independent Variables (X)			Dependent variable at different times (Y_1)				
	X_1	……	X_1	Y_1at t	Y_1 at t-1	….	…	Y_1at t-p
1								
2								
…								
u								
…								
k								

Data for each sets of X and a single Y would be required and a linear regression analysis can be done to estimate the parameters. Data can be collected for each set of a single dependent variable and one or more independent variables and equation (5.3) can be rewritten as:

$$\begin{bmatrix} y_t^1 \\ \vdots \\ y_t^k \end{bmatrix} = \begin{bmatrix} 1 x_{11} & \cdots & x_{1\ q+p} \\ \vdots\ \vdots & \ddots & \vdots \\ 1 x_{k1} & \cdots & x_{k\ q+p} \end{bmatrix} \begin{bmatrix} \beta_0 \\ \vdots \\ \beta_{q+p} \end{bmatrix} + \begin{bmatrix} \mathcal{E}_1 \\ \vdots \\ \mathcal{E}_n \end{bmatrix} \quad (5.4)$$

Here y^k_t is the value of the dependent variable at time t from the k[th] project and X_{k1} is the value for the dependent variable X_1 from the k[th] project.

Equation (5.3) is a classical linear regression model.

$$Y_{(k\times1)} = X_{(k\times(q+p+1))}\beta_{((q+p+1)\times1)} + \mathcal{E}_{(k\times1)} \quad (5.5)$$

The above regression model has the following assumptions:

1. E(Ɛ) = 0; and

2. Cov(Ɛ) = E(Ɛ Ɛ’) = $\boldsymbol{\sigma}^2$I.

The values of X and Y can be used from the historical data and the parameter β can be estimated as follows:

$$\beta = (X'X)^{-1}X'y \quad (5.6)$$

The parameters can also be estimated by using statistical software such as SAS. After fitting the model, goodness of fit can be tested by calculating coefficient of determination, r^2. This result is also obtained using statistical software.

5.3 NUMERICAL EXAMPLE

A part (highlighted in red) of the causal loop diagram (Figure 5.2) is used to illustrate model fitting.

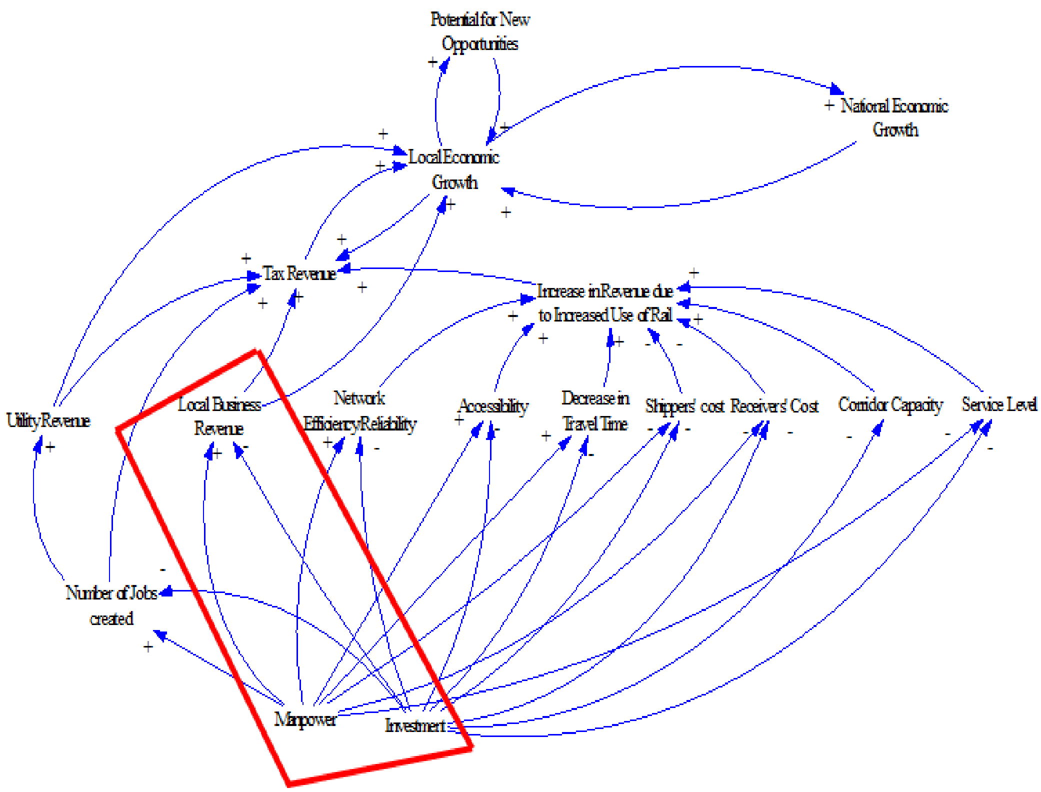


Figure 5.2 Causal Loop Diagram for Numerical Example

Assume that data were collected from 6 similar projects in history, shown in Table 5.3. Here X_1 is the money invested, X_2 is the manpower hired and Y_1 is the increase in local business revenue at time t for 5 time periods. X_1 and X_2 are constants for each project and the output, Y is dynamic, i.e. keeps changing with time.

Table 5.3 Data for Numerical Example

#	Independent Variable		Dependent variable at different times				
	X_1	X_2	Y_1 at t	Y_1 at t-1	Y_1 at t-2	Y_1 at t-3	Y_1 at t-4
1	10,000,000	40	300,000	265,000	215,000	145,000	100,000
2	15,000,000	48	400,000	350,000	275,000	225,000	175,000
3	5,000,000	24	180,000	140,000	110,000	80,000	55,000
4	8,000,000	30	250,000	210,000	175,000	115,000	90,000
5	17,000,000	55	450,000	385,000	325,000	260,000	210,000
6	22,000,000	60	700,000	650,000	585,000	520,000	475,000

Using the transformations from equation (5.1) and (5.2), the data from Table 5.3 can be used in equation (6.3) as:

$$\begin{bmatrix} 300\,k \\ 400k \\ 180k \\ 250k \\ 450k \\ 700k \end{bmatrix} = \begin{bmatrix} 1 & 10{,}000k & 40 & 265\,k & 215k & 145k & 100k \\ 1 & 15{,}000k & 48 & 350\,k & 275k & 225k & 175k \\ 1 & 5{,}000k & 24 & 140\,k & 110k & 80k & 55k \\ 1 & 8{,}000k & 30 & 210\,k & 175k & 115k & 90k \\ 1 & 17{,}000k & 55 & 385\,k & 325k & 260k & 210k \\ 1 & 22{,}000k & 60 & 650\,k & 585k & 520k & 475k \end{bmatrix} \times \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \\ \beta_5 \\ \beta_6 \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \\ \varepsilon_6 \end{bmatrix}$$

Using SAS (Appendix B) the results for the parameters are obtained as shown in Table 5.4.

Table 5.4 Model Fitting Results (Matrix β)

β_0 =	50048
β_1 =	0.00805
β_2 =	149.07649
β_3 =	0.20684
β_4 =	0.32381
β_5 =	0.26919
β_6 =	0

The fitted model can now be applied to equation (5.3).

From SAS results (Appendix B), coefficient determination, r-square is equal to 1.which means the fitted model explains all variability.

6. CONCLUSION

To quantify economic benefits of investment in rail infrastructure projects, three different approaches, namely Leontief approach, Bayesian approach and System Dynamics approach were studied. The possible metrics for investment in rail infrastructure projects (Table 1.1) were used to develop mathematical models using the three approaches.

The Leontief-based model was fitted via multivariate regression. The Leontief-based approach is the simplest of the three approaches if historical data of similar projects are available. Not only does it involve a simple system of linear equations, but it can easily be applied in the absence of reliable multipliers. Historical data on input and output variables can be used to arrive at fairly good multipliers that can be further used to calculate the project deliverables. One simplifying assumption used in this approach is that relationships between the various factors are linear. This method is fairly easy to use. The interdependencies among the various factors can be studied using this framework.

In the Bayesian approach, the metrics are divided into three sets of variables, i.e., decision variables, evaluation criteria and objective variables. The framework developed here helps to understand the relationships between various factors and studies the effects on the output variables when different sets of decision variables are considered. For this approach, it is very important to form a panel of experts and also conduct surveys to gather data for the approach. The expert panel must contain individuals from each stakeholder group. The entire data gathering approach, including the important design variables that affect the process, is subjective, and hence without careful consideration there is scope for large errors. Getting experts' opinion can be a tedious and expensive process and sometimes experts are not available for some stakeholder group and there is a risk of gathering misleading data. It is extremely important to have the appropriate number of experts from all the different subsystems to have reliable data. If the data are unreliable, there may be significant variation, especially when applied to the future distributions of variables. Also, solving a Bayesian network can be complex and many decision-makers find it hard to use. The major advantage of Bayesian approach is that it is suitable for small data sets as the missing data can be filled using expert opinions. Also, due to the probabilistic nature of data, this technique allows for estimation of risk [48]. The Bayesian method provides a sophisticated approach to analyze the impact of modification in the rail infrastructure. It has the ability to combine prior knowledge based on causal forms and observed data to predict the impact. Even in the case of missing data, it can be used to study the causal relationships and gain a better understanding of different problem domains. Based on previous data values, a Bayesian network can be used to predict future events as well. [49], [28]. Bayesian frameworks provide decision makers with a range of likelihoods of outcomes and also allow for improved estimates as more information becomes available as the investment process unfolds. Hence, decision makers can make adjustments in their decisions as additional information appears.

The third approach described in this report is the System Dynamics approach that takes into account the different metrics and the relationships between these metrics. This approach provides a good framework to begin with, but during the process of defining the equations and analyzing it quantitatively the model gets complex to solve. The causal loop diagram for Missouri rail project is represented in Figure 5.1 in this report. The CLD provides a good framework to visually represent the interactions between various elements. The correlation between various elements should not be confused with causality as this may lead to terrible misjudgments and policy errors [50]. Moreover, extra care must be taken while considering causal relationships in the model even if the correlation is strong or even if the coefficients in a regression are highly significant as this may lead to misleading results which is why incorporating the experts' opinions and the results from surveys are critical in understanding the causal relationship. The System Dynamics approach looks at the time series of each of the variables involved. However, in the absence of good multipliers, the equations used to solve the dynamic model can be highly unreliable. In the absence of numerical data, judgmental estimates can be made based on the available information and which can be later validated by doing a sensitivity analysis. To estimate the parameters in system dynamics approach engineering data are required and expert interviews and surveys need to be done which might turn out to be a tedious and an expensive process. Finally it can be said that the system dynamics approach is a fairly straightforward and easy method for developing a visual framework to study the interactions and interdependencies between various elements, but quantitative analysis using this approach can become very complex.

Table 6.1 compares the three approaches used to model the socio-technical factors for rail infrastructure investment process.

Table 6.1 Model Comparisons

Criteria for comparison	Leontief Approach	Bayesian Approach	System Dynamics Approach
Data Availability	Historical data are required to solve the method	Can be used even when small data sets are available	Time-series data are required in this approach
Parameter Estimation	Estimated from historical data using regression analysis	Estimated after conducting expert interviews and surveys	Estimated from expert opinions, surveys and engineering data using regression analysis
Relevance to Railroad Infrastructure Investment	Highly relevant	Highly relevant	Highly relevant
Ease of Application	Straightforward method and easy to use	Easy to apply given the availability of expert opinions	Qualitative analysis is straightforward and easy, but quantitative analysis may get very complicated

In conclusion, the development of Leontief models can serve as a first step in a long term investment plan to steer the project in the right direction and give a general idea of the impact of the various metrics involved. Also, the development of mechanism to regularly obtaining and updating economic, demographic, and attitudinal data needs to be formed to provide better data set to be used in these models.

The foundation based on the Leontief models can then be bolstered by modeling approaches based on the Bayesian and System Dynamic models to account for the long-term variability in metrics that affect railroad infrastructure.

APPENDIX A

LEONTIEF MODEL EXAMPLE - SAS CODE AND RESULTS

SAS Code for Leontief Approach

The SAS code used for fitting the model using Leontief approach is given below:

```
data mra;
input x1 x2 y1 y2 y3 y4 y5 y6 y7 y8 y9 y10 y11;
datalines;
10000000 40 46 200000 800000 20000 30 20 15000 17000 0.16 0.20 0.1
15000000 48 54 300000 1200000 30000 45 30 22000 24000 0.24 0.30 0.15
5000000 24 31 100000 400000 10000 15 10 6000 8000 0.08 0.10 0.05
8000000 30 37 160000 650000 16000 24 16 9000 11000 0.10 0.16 0.08
3000000 14 19 60000 250000 6000 8 6 2000 4000 0.03 0.06 0.03
22000000 60 74 440000 1800000 44000 65 44 37000 41000 0.35 0.44 0.22
17000000 55 63 350000 1400000 34000 53 35 33000 36000 0.29 0.34 0.17
12000000 44 52 250000 1000000 24000 36 25 18000 23000 0.19 0.24 0.12
9000000 35 42 180000 750000 18000 27 18 12000 15000 0.13 0.18 0.09
6000000 28 34 140000 500000 13000 18 14 8000 10000 0.11 0.12 0.06
proc glm data = mra;
model y1 y2 y3 y4 y5 y6 y7 y8 y9 y10 y11= x1 x2 /ss3;
manova h = x1/printe;
manova h = x2/printe;
run;
```

SAS Results for Leontief Approach

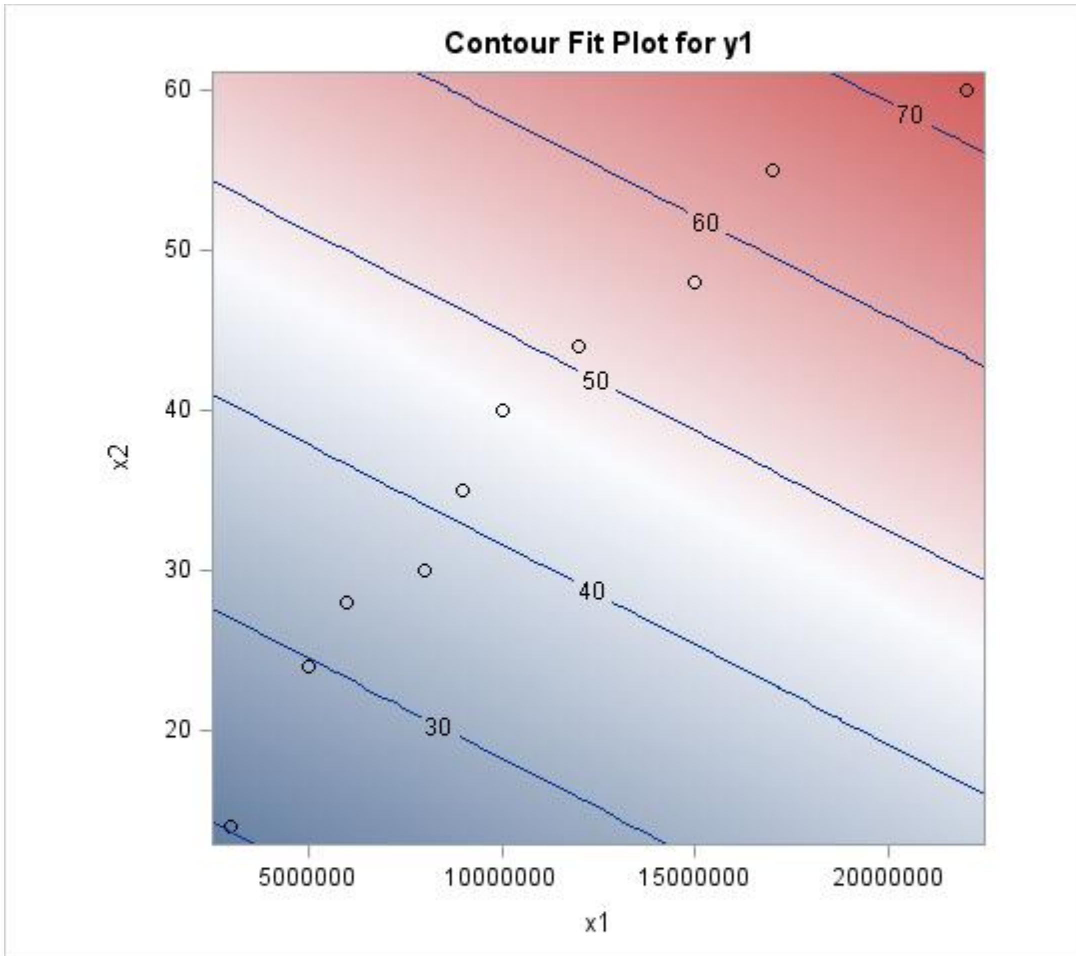
The following results were obtained using SAS and the parameter estimates for each variable are highlighted in yellow.

The SAS System

The GLM Procedure

Dependent Variable: y1

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	6.982274447	2.29704132	3.04	0.0189
x1	0.000000934	0.00000040	2.31	0.0541
x2	0.746586559	0.16569921	4.51	0.0028

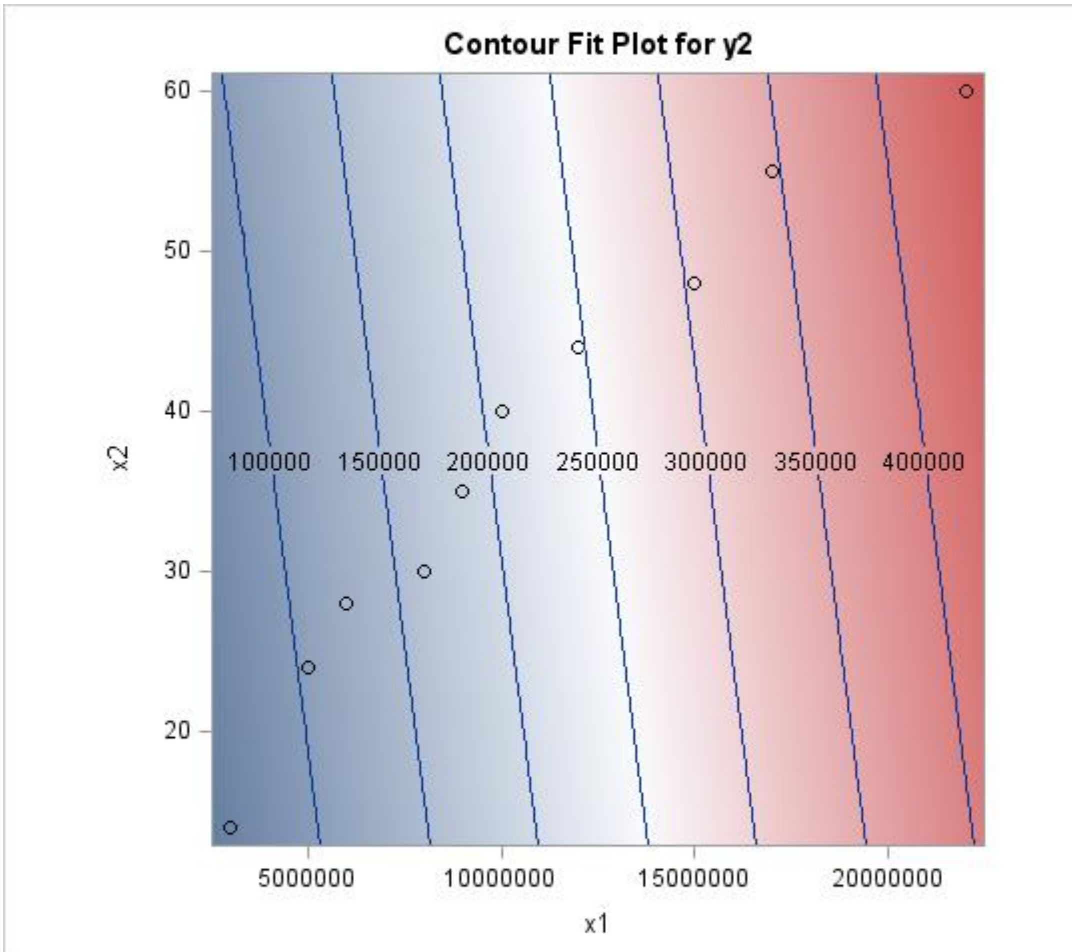


The SAS System

The GLM Procedure

Dependent Variable: y2

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-6845.913829	10720.35855	-0.64	0.5434
x1	0.017725	0.00189	9.39	<.0001
x2	930.941896	773.32300	1.20	0.2678

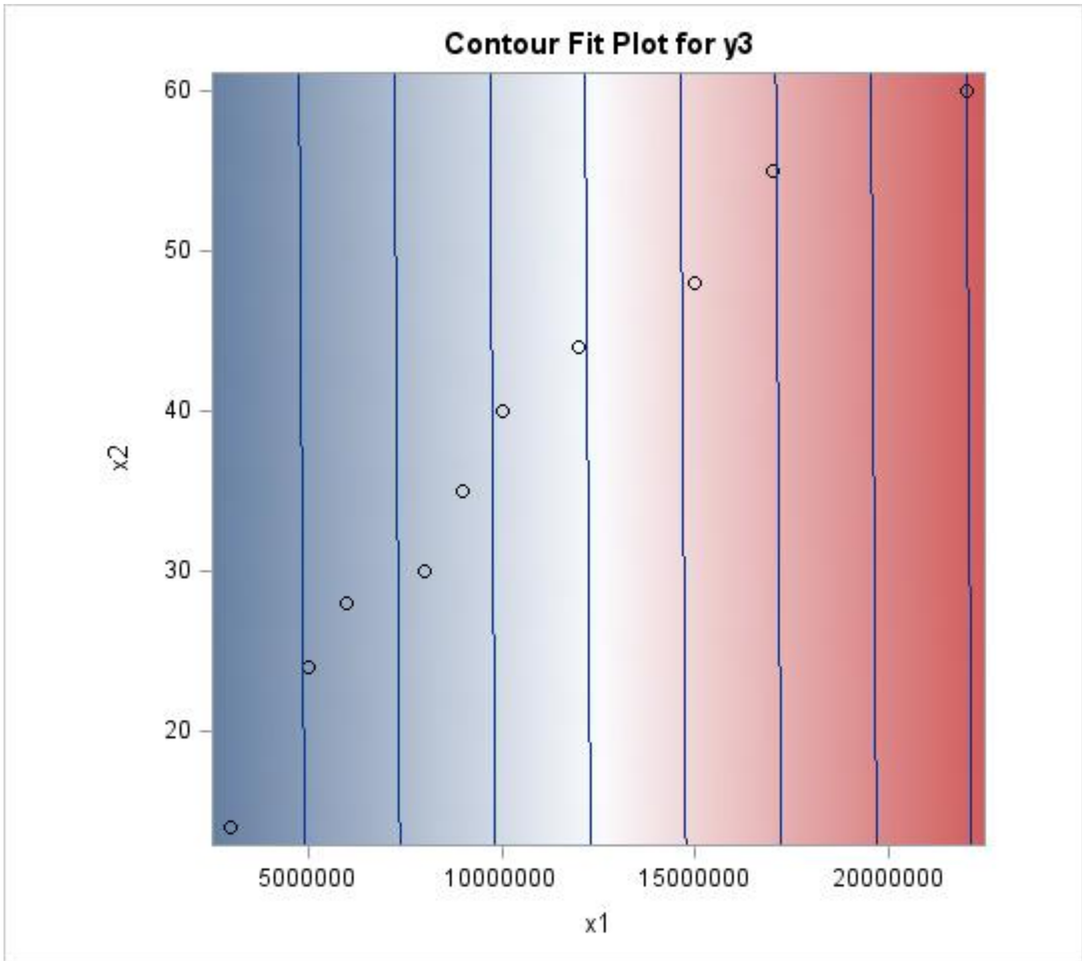


The SAS System

The GLM Procedure

Dependent Variable: y3

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-1268.007701	24254.89243	-0.05	0.9598
x1	0.081066	0.00427	18.99	<.0001
x2	234.385949	1749.64916	0.13	0.8972

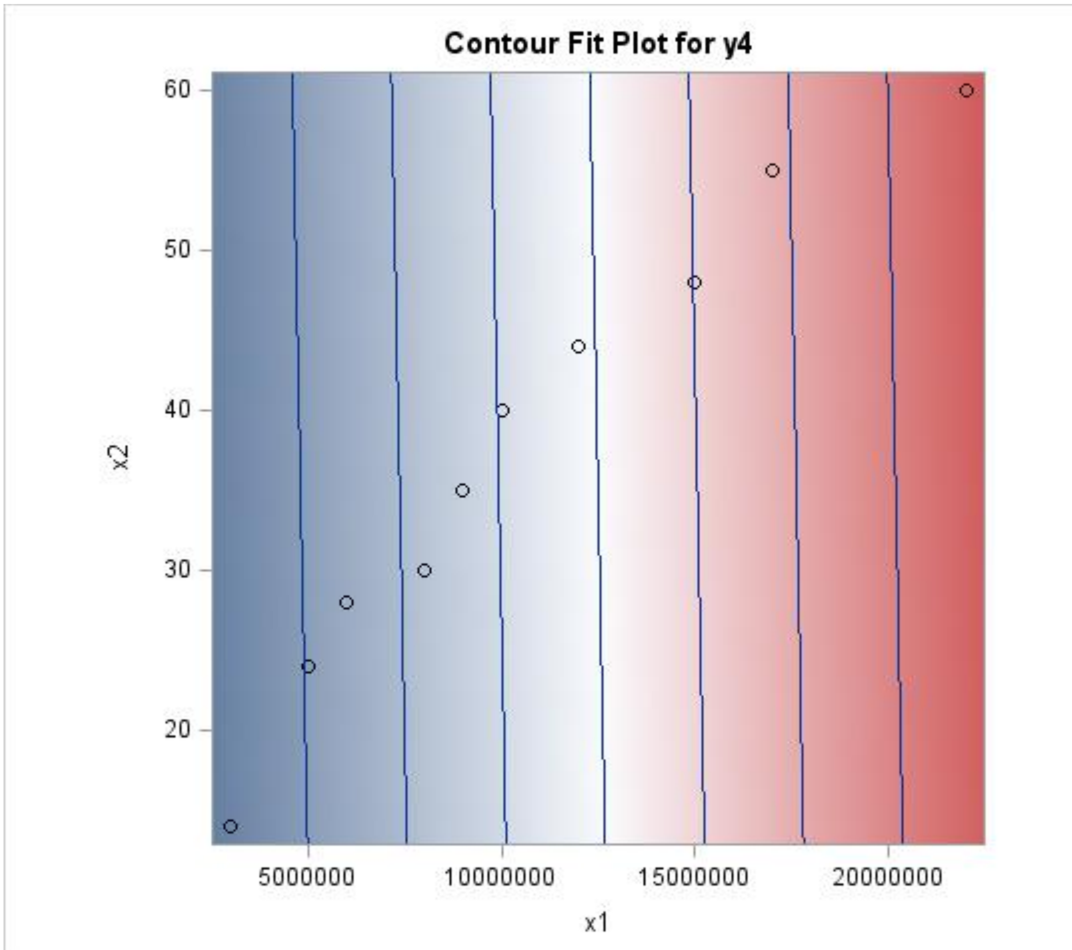


The SAS System

The GLM Procedure

Dependent Variable: y4

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	63.40038505	504.9428785	0.13	0.9036
x1	0.00194669	0.0000889	21.91	<.0001
x2	16.05848031	36.4245227	0.44	0.6726

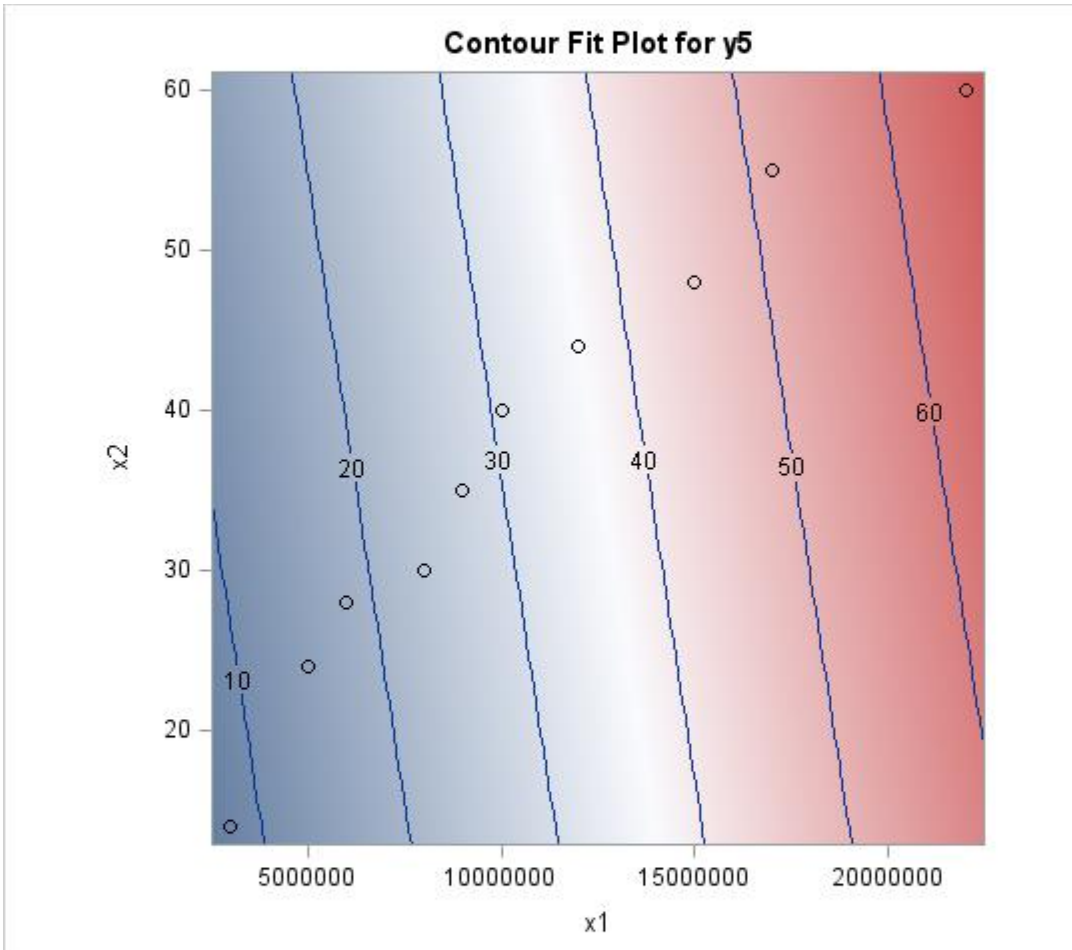


The SAS System

The GLM Procedure

Dependent Variable: y5

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-2.372634933	1.02109929	-2.32	0.0531
x1	0.000002630	0.00000018	14.63	<.0001
x2	0.167629290	0.07365794	2.28	0.0570

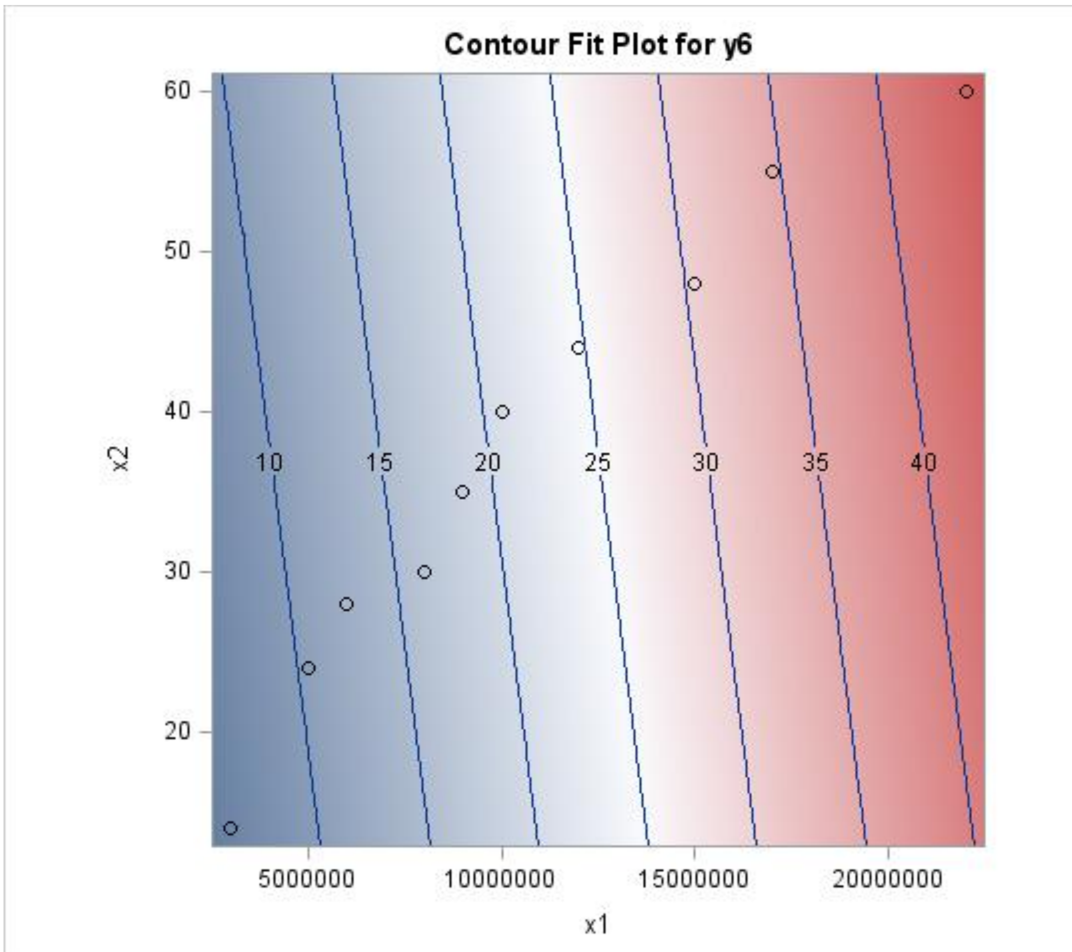


The SAS System

The GLM Procedure

Dependent Variable: y6

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-.6845913829	1.07203586	-0.64	0.5434
x1	0.0000017725	0.00000019	9.39	<.0001
x2	0.0930941896	0.07733230	1.20	0.2678

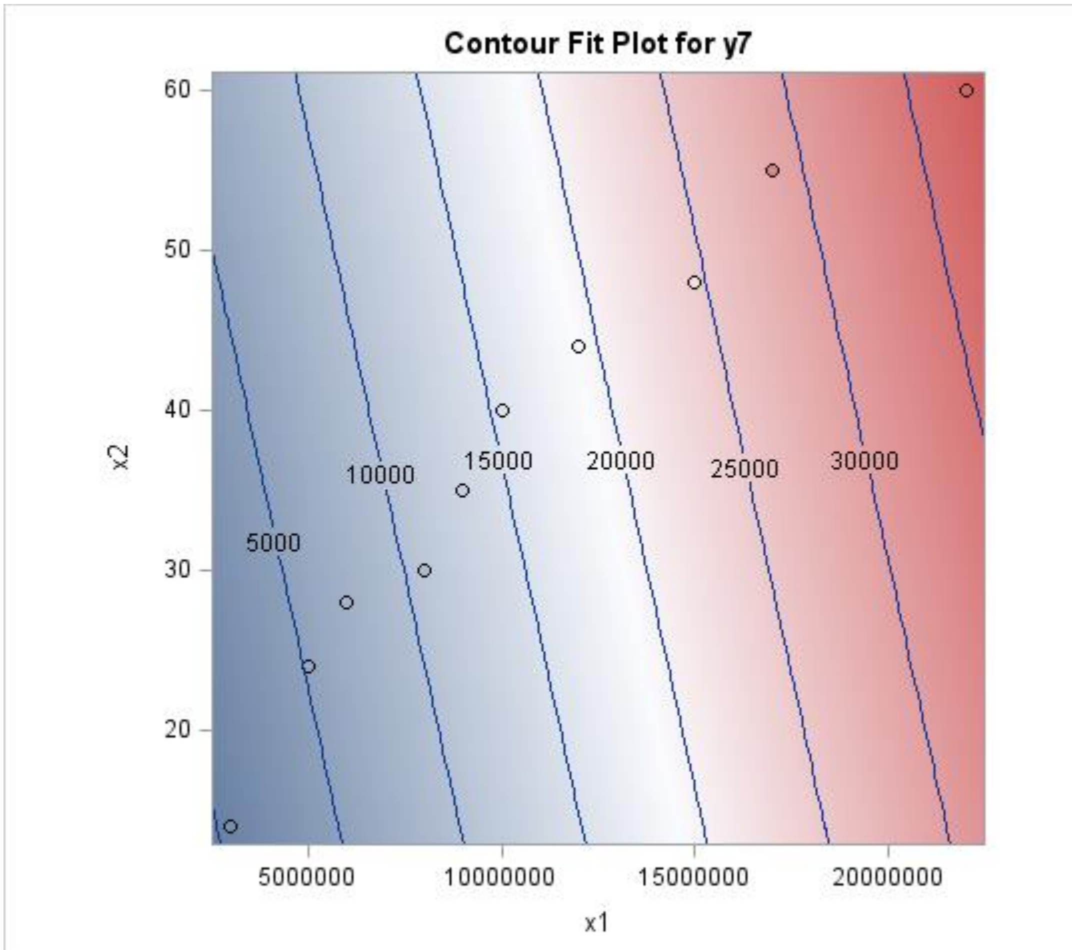


The SAS System

The GLM Procedure

Dependent Variable: y7

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-6187.213702	3286.767849	-1.88	0.1018
x1	0.001587	0.000578	2.74	0.0288
x2	143.098984	237.094046	0.60	0.5652

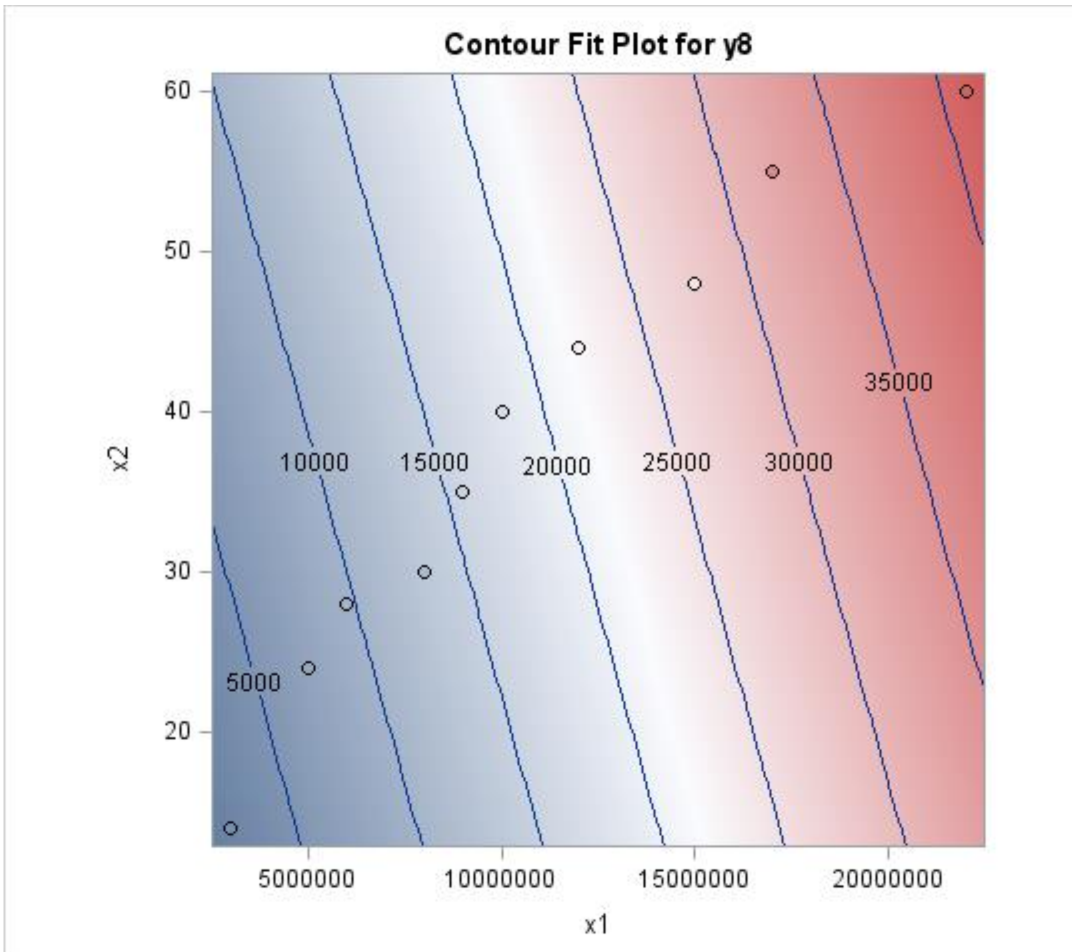


The SAS System

The GLM Procedure

Dependent Variable: y8

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-5024.297949	3529.126520	-1.42	0.1976
x1	0.001595	0.000621	2.57	0.0371
x2	181.338379	254.576814	0.71	0.4993

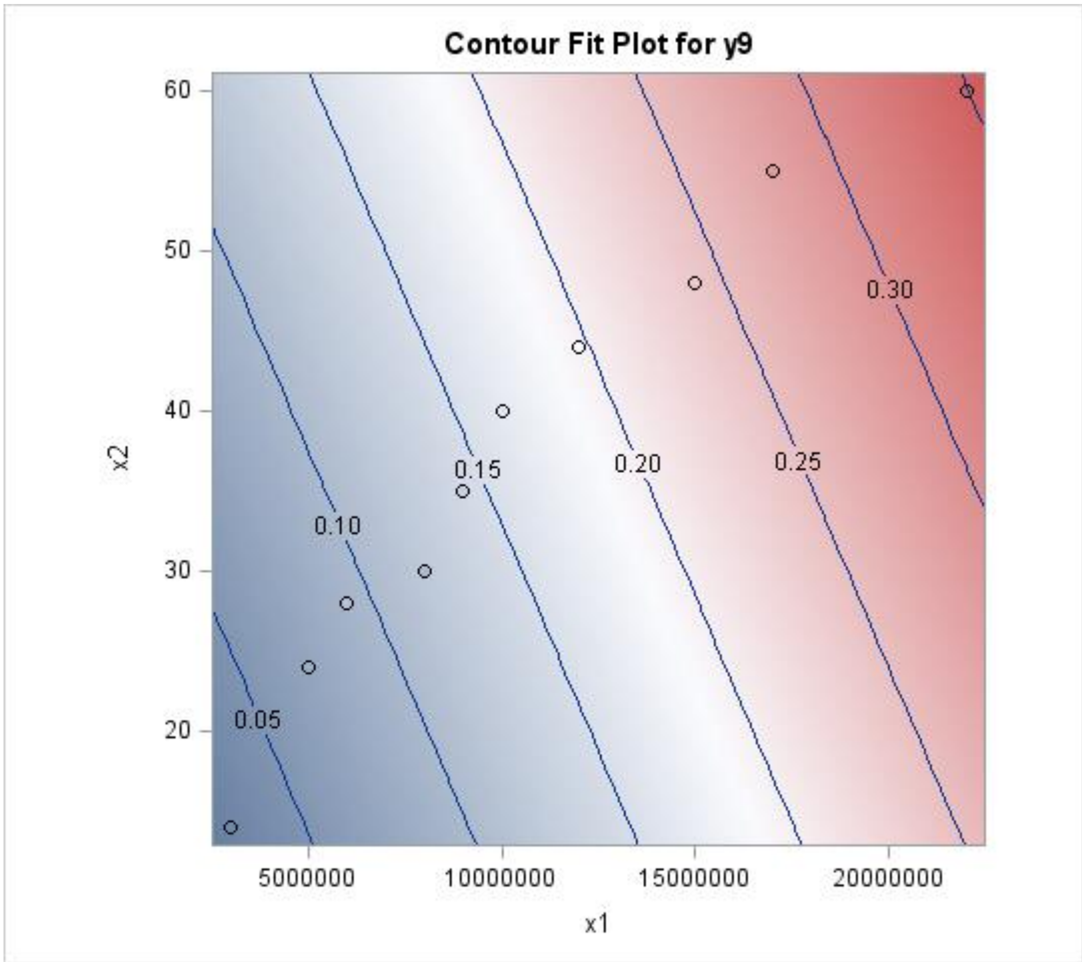


The SAS System

The GLM Procedure

Dependent Variable: y9

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-.0378311093	0.01892865	-2.00	0.0858
x1	0.0000000119	0.00000000	3.56	0.0092
x2	0.0020874549	0.00136544	1.53	0.1702

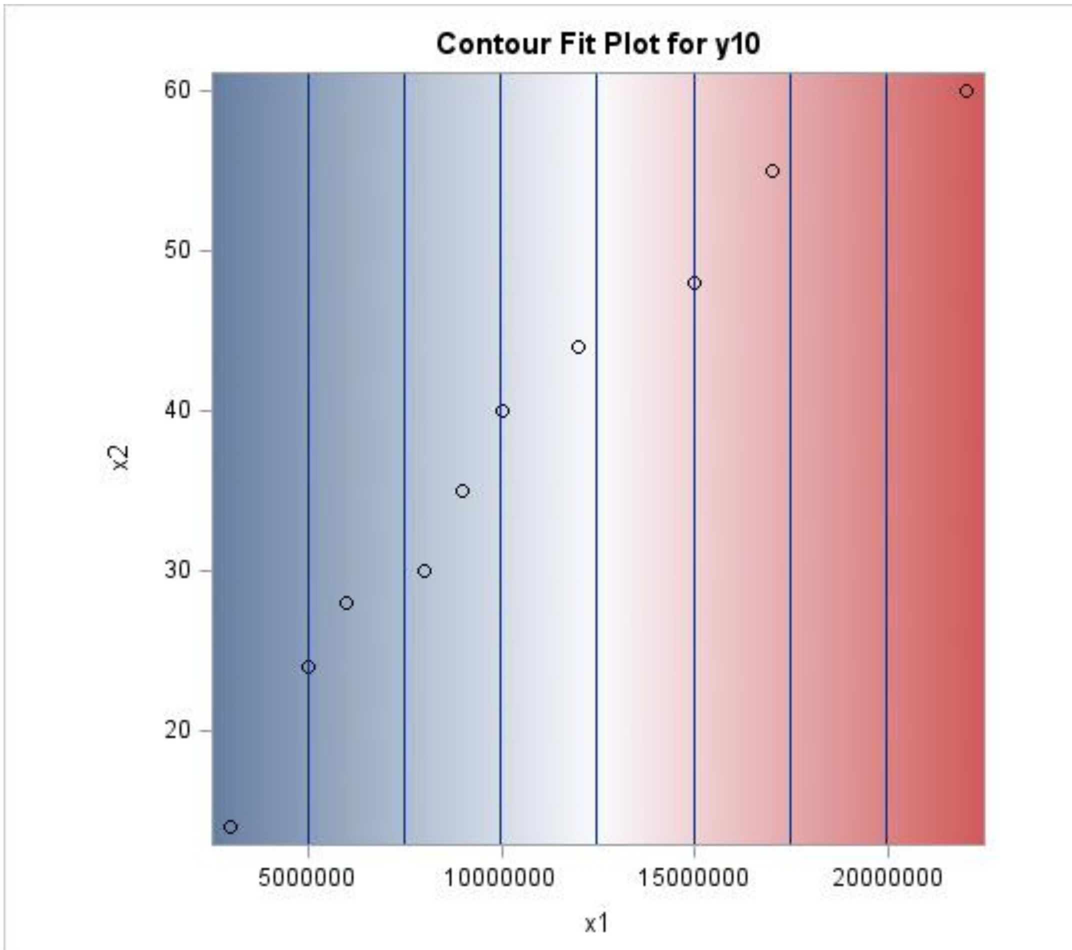


The SAS System

The GLM Procedure

Dependent Variable: y10

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-8.04912E-16	0	-Infty	<.0001
x1	2E-8	0	Infty	<.0001
x2	6.134247E-17	0	Infty	<.0001

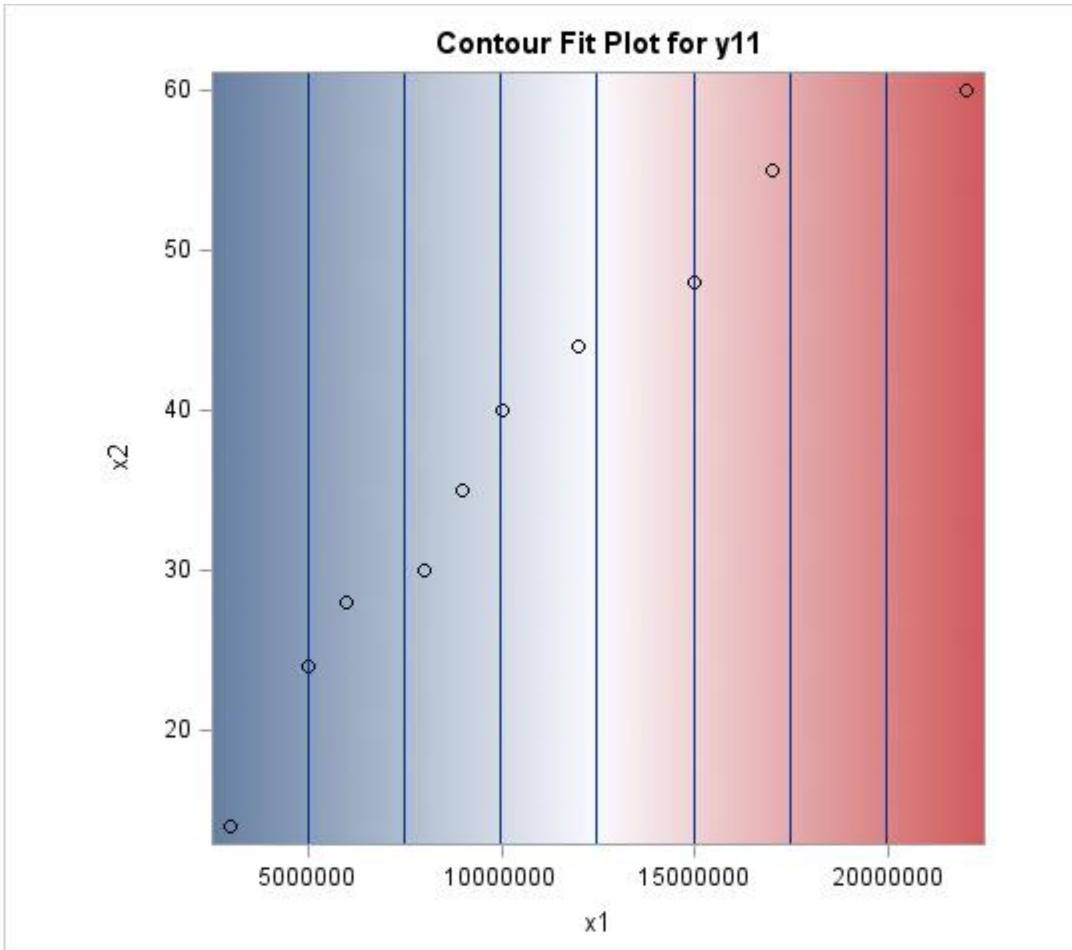


The SAS System

The GLM Procedure

Dependent Variable: y11

Parameter	Estimate	Standard Error	t Value	Pr > |t|
Intercept	-4.02456E-16	0	-Infty	<.0001
x1	1E-8	0	Infty	<.0001
x2	3.067123E-17	0	Infty	<.0001



APPENDIX B

SYSTEM DYNAMICS MODEL EXAMPLE - SAS CODE AND RESULTS

SAS code for System Dynamics Approach

```
data railroad;
input x1 x2 y1 y2 y3 y4 yt;
datalines;
10000000 40 265000 215000 145000 100000 300000
15000000 48 350000 275000 225000 175000 400000
5000000 24 140000 110000 80000 55000 180000
8000000 30 210000 175000 115000 90000 250000
17000000 55 385000 325000 260000 210000 450000
22000000 60 650000 585000 520000 475000 700000
proc reg data = railroad;
model yt = x1 x2 y1 y2 y3 y4;
run;
```

SAS results for System Dynamics Approach

The following results for the parameter estimation were obtained using SAS.

The SAS System

The REG Procedure

Model: MODEL1

Dependent Variable: yt

Number of Observations Read	6
Number of Observations Used	6

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	5	1.71E11	34200000000	.	.
Error	0	0	.		
Corrected Total	5	1.71E11			

Root MSE	.	**R-Square**	1.0000
Dependent Mean	380000	**Adj R-Sq**	.
Coeff Var	.		

y4 = 19421.5 * Intercept + 0.00568 * x1 - 2418.94 * x2 - 0.42594 * y1 + 0.45416 * y2 + 0.93655 * y3

Parameter Estimates

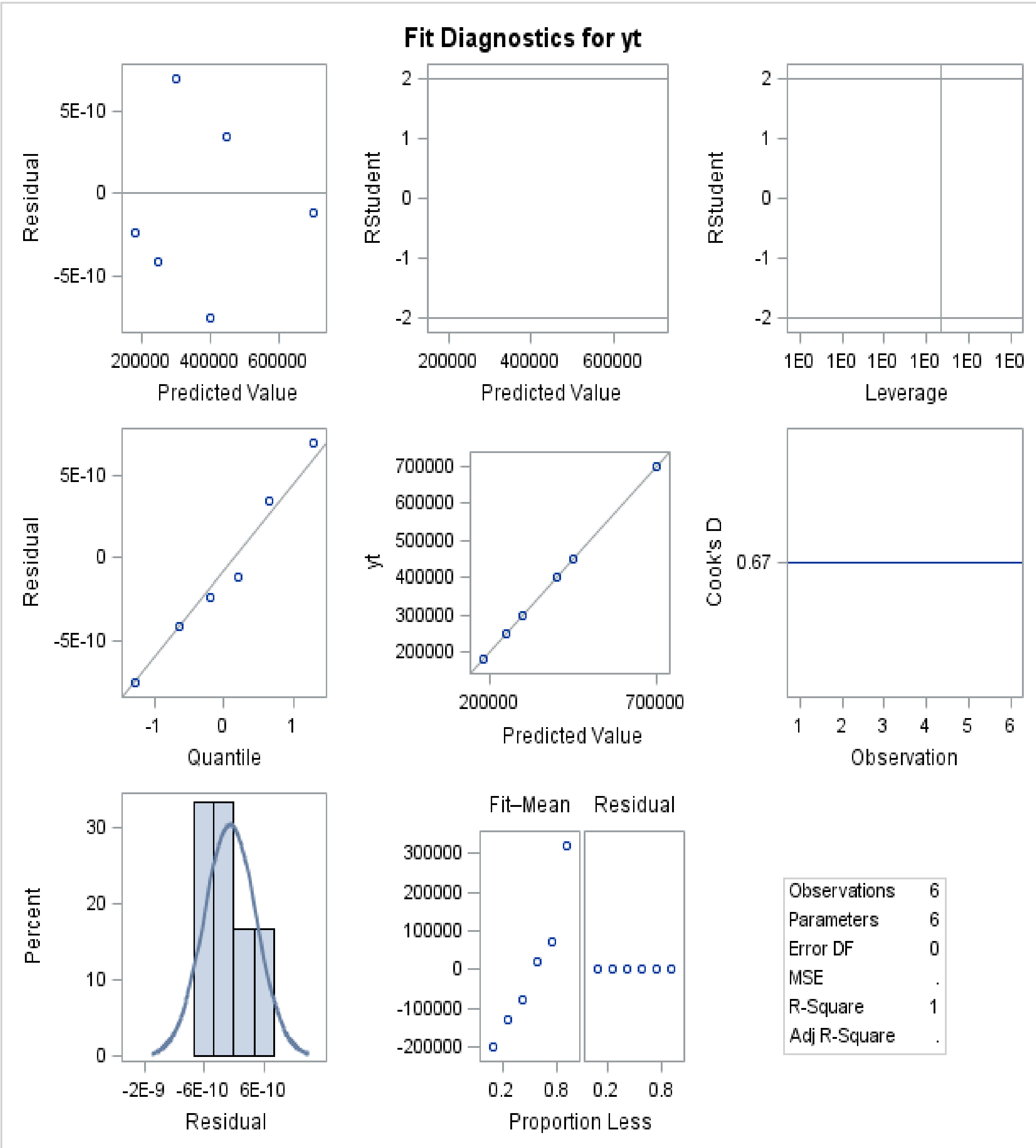
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	**B**	50048	.	.	.
x1	**B**	0.00805	.	.	.
x2	**B**	149.07649	.	.	.
y1	**B**	0.20684	.	.	.
y2	**B**	0.32381	.	.	.
y3	**B**	0.26919	.	.	.
y4	**0**	0	.	.	.

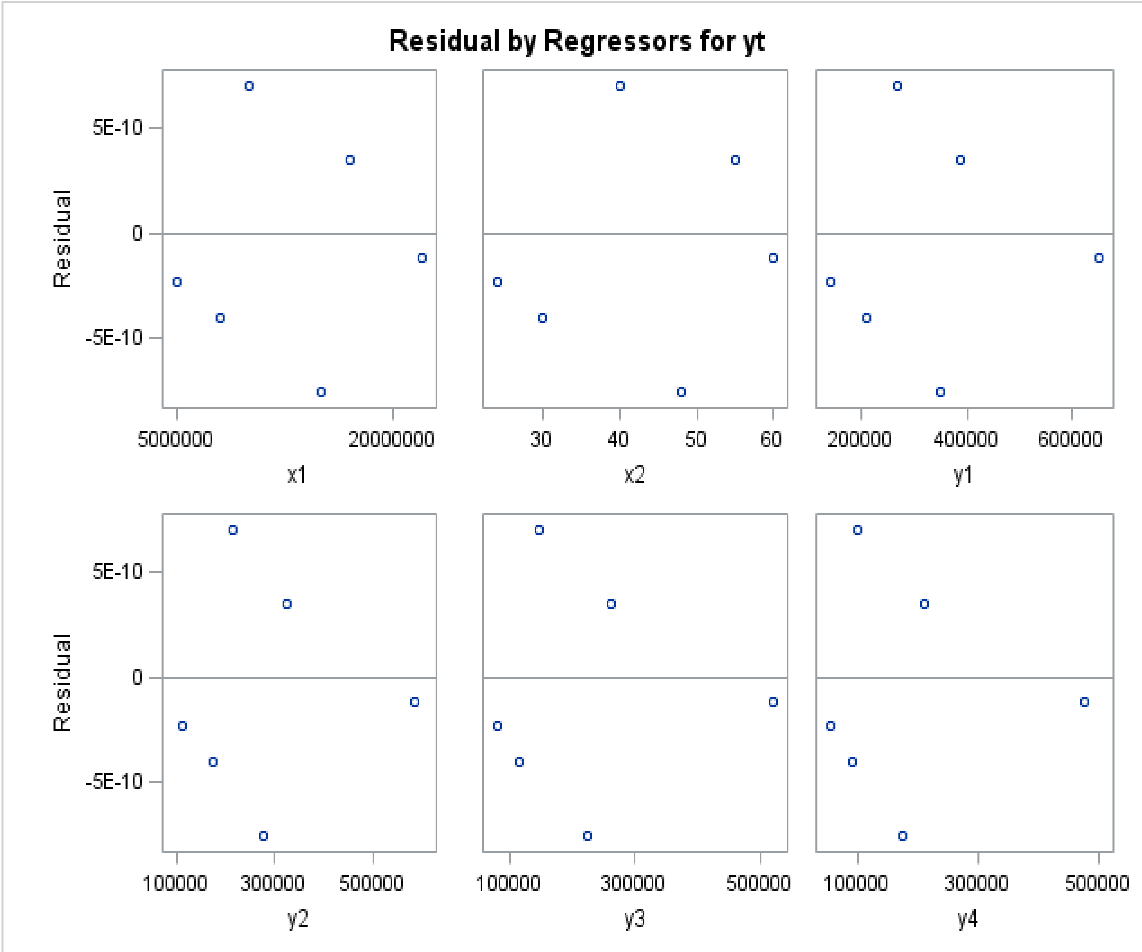
The SAS System

The REG Procedure

Model: MODEL1

Dependent Variable: yt




Residual by Regressors for yt
Residual
5E-10
0
-5E-10
5000000
20000000
x1
30
40
50
60
x2
200000
400000
600000
y1
100000
300000
500000
y2
y3
y4

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