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An optimization model for land allocation between bioenergy crops and grain crops and an optimization model for identifying the most vulnerable links in a transportation network

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An optimization model for land allocation between bioenergy crops and grain crops and an optimization model for identifying the most vulnerable links in a transportation network

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DEDICATION

I would like to dedicate this thesis to my family without whose support I would not have been able to complete this work. I would also like to thank my friends for their loving guidance during the writing of this work.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

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ABSTRACT

This thesis consists of two separate studies. The first part is for land allocation between grain crops and bioenergy crops. The second part is for identifying most vulnerable links in a transportation network. Optimization models are used in both studies.

The first part of this thesis focuses on analyzing farmers' land allocation between bioenergy crops and grain crops and the impact of bioenergy crop contract price on farmers' land allocation. An optimization model for a centralized farmer is proposed. The model simulates farmers' objective by maximizing their profits. Under the consideration of crop rotation constraints, farmers' land allocation is optimized. A case study including corn, soybean and switchgrass for Iowa is conducted. Our model can compute the threshold of switchgrass contract price, which can provide guidance in contract negotiation between farmers and bioenergy producers.

The second part of the thesis concerns identifying the most vulnerable links in a transportation network. The problem can be viewed as a game between an "attacker" and network users. The attacker represents natural disasters or man-made accidents that could reduce network capacity, whereas network users decide their travel patterns in response to the attacker's action. By maximizing the attacker's disruption to the network, our model can identify the most vulnerable links in the network, which provides the most effective strategy to strengthen the robustness of the network. We conducted a case study for a sixteen-link network with two demand scenarios and the most vulnerable links are found. For that particular network, reducing the most vulnerable 0.7% of total capacity doubles the system travel time. Therefore, maintaining full capacity on these most vulnerable links is crucial for the system.

CHAPTER 1. GENERAL INTRODUCTION

1.1 Introduction

This thesis concentrates on two topics: (1) an optimization model for land allocation between bioenergy crops and grain crops; (2) an optimization model for identifying most vulnerable links in a transportation network. In this chapter, some background for the two topics is briefly introduced.

1.1.1 Bioenergy crops vs. grain crops

Much work within agricultural economics is concerned with crop selections. For a certain piece of land, it is usually suitable to choose several types of crops. Farmers make crop selections based on criteria including prices, government policy and a host of environmental factors [22]. Major grain crops as the most common annual crops are traditionally selected by farmers. Farmers' profit from grain crops is subject to two major sources of uncertainty: yields and grain prices. The former is primarily determined by weather conditions, whereas the latter is influenced by numerous market factors. Severe weather such as drought and floods result in great grain production loss. Market turbulence due to big events such as financial crisis of 2008 can lead to low prices of grains. The uncertainty of farmers' profit is reduced by crop insurance, which provides protection when either yields or prices are too low. Under the protection of crop insurance, the uncertainty of grain yields and prices still exists.

Widely known is that bioenergy crops can bring some ecological benefits. Moreover, bioenergy crops are raw materials for bioenergy production. Bioenergy as a type of clean energy, can significantly reduce greenhouse gas emissions. The existing dry grind ethanol facilities in the United States have the potential to create over 1.5 billion gallons of cellulosic ethanol [3] while the Renewable Fuels Standard (RFS) sets an annual goal of 16 billion gallons by 2022. In order to achieve RFS goal, there is a great demand for bioenergy crops as raw materials of cellulosic ethanol. Walsh [33] pointed out that bioenergy crops could potentially be produced at a profit greater than existing agricultural land use. Therefore, bioenergy crops are becoming new choices for farmers. With the emergence of bioenergy crops, competition between grain crops and bioenergy crops begins. Different from grains which have a mature market, bioenergy crops don't have a market and are supported by some special government policies. Those policies state farmers make profit by signing contracts without undertaking any risks. And many kinds of selectable bioenergy crops are perennial plants. If farmers want to get involved in bioenergy crops, they need to sign the contract with bioenergy companies or government agencies. The most common contract is provided by Conservation Reserve Program (CRP) [4].

It is difficult to optimize land allocation between bioenergy crops and grain crops. In Midwest, corn and soybean are typical grain crops while switchgrass is representative of bioenergy crops. Farmers who want to plant switchgrass need to sign the contracts in advance. Typical contract for switchgrass lasts for five years. Farmers make decisions for corn and soybean depending on the prices, yields and market demand year by year. Besides, farmers have to undertake the cost and consider corn and soybean rotation if they assign their land for corn and soybean.

We can find related work in literatures. Kanhan [20] addressed that weather change, prices and government policy are risks for farming. Aimin [8] explored the elements, which affect farmers' decision under risk. Some work is done on crop acreage under the consideration of price and yield. Finger [16] provides policy makers with accessible risk management tools to support farmers. Fabiosa [14] proposed a model incorporating trade-offs between biofuel, feed, and food production and consumption and international feedback effects through world prices and trade. In [28], an estimation of the aggregate totals of land use change is given.

1.1.2 Identifying most vulnerable links in a transportation network

In recent years, transportation network vulnerability is widely discussed. For the complexity of transportation network, there are various indicators to assess the vulnerability within the system. Literatures concerned about reliability, risks and accessibility are proposed to give explicitly description for transportation network vulnerability. In [11], Berdica interpreted reliability, risks and accessibility in a transportation network, emphasizing the road transportation system susceptibility to incidents that can result in reduction in road network serviceability. Murray [26] proposed that network vulnerability demonstrates the consequence of link failures. Generalized travel cost is proposed to judge vulnerability in [32] while Jenelius [19] utilized the increase of generalized travel costs weighted by satisfied and unsatisfied demand when network links are closed.

Emerging methodologies from determining vulnerable links to identifying vulnerable sections for transportation network gave quantitative analysis for transportation network vulnerability assessment [27, 31]. Murray [27] developed a bilevel formulation to identify vulnerable transportation network links. The transportation network vulnerability assessment identification problem can be viewed as a game between an "attacker" and users. An attacker in reality, can be enemies, natural disasters or accidents, which have power to cause failures for the transportation network. Considering the network failures, users travel with flows that are simulated by traffic assignment problem of the system. We address the problem in two aspects: (1) from attacker's perspective, how to interdict the transportation network with certain budget for an attacker causing the maximum disruption (2) from system perspective, how users respond to a reduced network. The purpose of analyzing attackers' perspective is not to help attackers to disrupt the system but to identify the worst case of system performance.

Maximizing disruption in transportation network can be interpreted as maximizing generalized travel cost. Generalized travel cost for transportation network is the sum of system travel time and monetary expense in [23]. Monetary expense for transportation network typically comes from toll road projects [36, 12, 15]. Literatures in transportation network addressed system travel time as generalized travel cost in some situations. Leurent [23] implemented a case without considering monetary expense in the test network.

Traffic assignment problem concerns with the traffic flow pattern in routes between origins and destinations. It simulates users' travel through a transportation network. Traffic assignment is a traffic flow prediction procedure, which helps for traffic monitoring, network design etc. Wardrop's first principle [35] states that the travel time in all routes are equal and less than those which would be experienced by a single user on any unused route. This principle gives an intuitive equilibrium for transportation a network that users all travel with the shortest travel time route. For approximately six decades, Beckmann's mathematical programming formulation of Wardrop's first principle of static traffic assignment has been applied to various traffic assignment problems [9]. Static traffic assignment problems using Wardrop's first principle can be formulated as mathematical programming problems in [25, 24]. Friesz [17] proposed a dynamic generalization of static Wardrop user equilibrium. Since there is uncertainty in traffic assignment problems, Daganzo [13] developed a stochastic user equilibrium as an extension of Wardrop's user equilibrium. Bell [10] emphasized the risk averse user equilibrium traffic assignment based on static Wardrop's user equilibrium. Network design problem, which aims at minimizing generalized travel cost has a bilevel hierarchy. In network design problems, upper level can manipulate expansion of the network while traffic assignment problem is utilized at the lower level to yield traffic flow. Work in [30, 34] used Wardrop's first principle to solve traffic assignment problem at the lower level.

1.2 Thesis Organization

This thesis is organized as follows. In chapter 2, an optimization model for land allocation between bioenergy crops and grain crops is built to estimate the bioenergy production in a large scale. Sensitivity analysis for bioenergy crop contract prices is conduct to analyze the contract price impact on bioenergy crop production. In chapter 3, an optimization model for identifying most vulnerable links in a transportation network is proposed. Vulnerable links in transportation network are identified under certain capacity reduction budget. Impact of capacity reduction budget on vulnerability is analyzed. Chapter 4 summarized the findings of this thesis and proposed future research work.

CHAPTER 2. AN OPTIMIZATION MODEL FOR LAND ALLOCATION BETWEEN BIOENERGY CROPS AND GRAIN CROPS

In this chapter, an optimization model for land allocation between bioenergy crops and grain crops is proposed. Farmers maximize the profits by planting grain crops and signing contract for bioenergy crops. Under the consideration of crop rotation constraints, the model is proposed to make an optimal land allocation between bioenergy crops and grain crops for farmers. And this model is used to analyze bioenergy crop contract price impact on the land acreage assigned to bioenergy crop for farmers. On the other hand, the model can be used to estimate land acreage assigned to bioenergy crops for bioenergy producers and help bioenergy producers to determine whether to modify bioenergy crop contract price.

2.1 Introduction

For a certain piece of land, which is suitable to several types of crops, it's difficult for farmers to quantify their decision making process. Land allocation, allows not only selecting or not selecting a crop on a piece of land but also determines the land acreage assignment for the crop. Land allocation makes the combination of different kinds of crops possible on a certain piece of land. In reality, farmers plant different kinds of crops on their land rather than stick to only one kind of crop for a whole year. Instead of only answering the question that which crop to plant as crop selection does, crop allocations consider both what to plant and how much land for the farming. Hence, land allocation provides farmers with more realistic decisions.

Grain crops, which are sources of food grain, are the most common crops around the world. Food grain is the major energy source for human. Typical food grain such as wheat, corn and soybean contain calories. It brings functional components and health benefits for human beings.

Food grain is indispensable to prevent human beings suffering from starvation. The demand for food grain has never decreased and the demand for grain crops never will decrease as long as that starvation is not wiped out. In developed countries, farmers make crop selections among grain crops based on criteria including prices, government policy and a host of environmental factors. Major grain crops are annual crops. Weather change, prices and government policy are risks for farming for grain crops. Severe weather such as drought and floods result in great grain production loss. Market turbulence can lead to low prices of grains. Crop insurance for grains can prevent farmers losing money if yields suffer from natural disasters and prices are too low. However, the grain crop yields and prices still experience variability. If profitability is the goal, farmers can optimize the land allocation for grain crops based on the future prices, yields and demands data.

With the emergence of bioenergy crops, farmers have new choices beyond grain crops. Bioenery crops are sources of bioenergy. Fossil fuels have dominated area of energy sources for years. But fossil fuels are formed by natural processes and the age of resulting in fossil is typical millions of years. It becomes an urge to develop energy source that is sustainable. Bioenergy is not only more sustainable but also more environmentally friendly. Bioenergy companies such as Dupont and Poet have a large demand for bioenergy crops. With the development of bioenergy crops, competition between grain crops and bioenergy crops begins. Different from grain crops, whose profits mainly depend on the market, bioenergy crops don't have market and are supported by government policies. Miscanthus Pilot Project for University of Iowa power plant states that farmers who are willing to implement bioenergy crops planting make profits before the farming begins without undertaking any risks. Many kinds of selectable bioenergy crops are perennial plants. Farmers need to sign the contract with bioenergy companies who will implement government's policies if they are involved in bioenergy crops. Contracts for bioenergy crops typically last for more than one year.

There are four types of farmers' identities [21]. Among the four farmers' identities, productivist farmers who aims at highest profit per acre can be well modeled. The reason is that maximizing the profit can be easily quantified. The decision making process for productivist farmers is straightforward. They optimize the land allocation to achieve their highest profit goal. The problem is that how to optimize the land allocation. What is the final profit objective formulation? What are the realistic constraint that farmers have? The profit objective relates with grain crop prices, yields, costs, insurance and bioenergy crop contract prices. An individual farmer can make profits by bioenergy crop contracts. Meanwhile, grain crops profit depends on the selling price and cost. Besides, agriculture research has found out useful crop rotation for grain crops. Farmers should follow the rotation rules in order to avoid some agricultural problems and obtain benefits. A centralized farmer who represent a large group of farmers should satisfy the grain crop market demands.

In terms of the bioenergy crop and grain crop land allocation, optimization can be an approach. In this optimization, bioenergy crops and grain crops are included. Given the price, yield and cost data, optimal allocations are made between bioenergy crops and grain crops under the rotation considerations.

2.2 Deterministic Model

2.2.1 Notations

Sets

- $\mathbb{T}$: set of farmers' decision making time points.
- $\mathbb{I}$: set of selectable grain crops.
- $\mathbb{J}$: set of selectable bioenergy crops.

Parameters

- P_i^t (\$/bushel): commodity prices for grain crop i in year t.
- S_i^t (\$/bushel): insurance protection prices for grain crop i in year t.
- P_j (\$/acre): contract price for bioenergy crop.
- Y_i^t (bushel/acre): yield for grain crop i in year t.
- C_i^{P} (\$/acre): preharvest cost for grain crop i.

- C_i^{H} (\$/bushel): harvest cost for grain crop i.

- r: interest rate.

- L (acres): total land acreage available for farming.

- d_i^t (bushel): market demand for grain crop i in year t.

- δ_{ik}: if $\delta_{ik} = 1$, grain crop i can be followed by grain crop k; if $\delta_{ik} = 0$, grain crop i cannot be followed by grain crop k.

Decision variables

- x_i^t: acreage assigned to grain crop i in year t.

- x_j^{B}: acreage assigned to bioenergy crop j.

2.2.2 Model formulation

This model is from a centralized farmer perspective. A centralized farmer represents a large group of farmers , for example: farmers in a state. Then, a centralized farmer should confront with market demands for grain crops. Given the prices and yields for grains and the contract prices for bioenergy crops, farmers must decide the best combination of selectable crops along the planting horizon. An individual farmer can make profits based on bioenergy crop contracts. Meanwhile, a farmer can select grains year by year facing up to yields and prices. If grains are selected, costs of planting are incurred. Preharvest cost is related to the land acreage for various grains. The harvest cost depends on the total yield of the products. Besides, if grain crops are selected, crop rotations are considered. Hence, the optimization model is:

$$\max_{x} \sum_{t=1}^{T} \frac{1}{(1+r)^t} \left[\sum_{j=1}^{J} P_j x_j^{\mathrm{B}} + \sum_{i=1}^{I} (max\{P_i^t, S_i^t\} Y_i^t x_i^t - C_i^{\mathrm{P}} x_i^t - C_i^{\mathrm{H}} Y_i^t x_i^t) \right] \tag{2.1}$$

$$\text{s. t.} \quad \sum_{i=1}^{I} x_i^t + \sum_{j=1}^{J} x_j^{\mathrm{B}} \leq L, \forall t \in \mathbb{T} \tag{2.2}$$

$$\sum_{k=1}^{I} \delta_{ik} x_i^t \geq x_i^{(t-1)}, \forall i \in \mathbb{I}, \forall t \in \mathbb{T} \tag{2.3}$$

$$Y_i^t x_i^t \geq d_i^t, \forall i \in \mathbb{I}, \forall t \in \mathbb{T} \tag{2.4}$$

$$x_i^t, x_j^{\mathrm{B}} \geq 0, \forall i \in \mathbb{I}, \forall j \in \mathbb{J}, \forall t \in \mathbb{T}. \tag{2.5}$$

It's assumed that the farmer belongs to productivist farmer identity category so profitability is the only goal. The model only includes annual grain crops that complete their life cycles within one year, and then die. We set the planting horizon as the bioenergy crop contract period. Besides, farmers land management follows procedures in [2]. The objective function (2.1) in this model is to maximize the profit of contracting the land for bioenergy crops and selling grains in the market. Hence, there are two parts in the objective function. One is the bioenergy crop contract return; the other is the profits by selling grains. Once the bioenergy crop contract is signed, a farmer accepts the the contract price that bioenergy plant gives and sticks to the contract along the planting horizon. Selecting grain crops is more complicate because farmers select grains every year depending on grain prices. Constraint (2.2) states that the farming scale of a farmer cannot exceed his considerable land acreage. In agriculture practice, crop rotation is common. Grain crops like soybean, cannot follow itself to avoid diseases issues even though prices for soybean in two years are both extremely high. Corn can take advantage of the nitrate that previous year's soybean leaves out. Thus, corn is a good follower for soybean. Therefore, if farmers only consider corn and soybean, this year's corn acreage should at least cover soybean acreage in the previous year. And that is what Constraint (2.3) claims. Farmers must satisfy the market demand for grain crops (2.4). Constraint (2.5) states that there are nonnegative variables.

2.3 Case Study

2.3.1 Data sources

In this case study, we take Iowa as a centralized productivist farmer who only considers corn and soybean as grain crops and switchgrass as the bioenergy crops in Iowa. Based on United States Department of Agriculture (USDA) long term projections released in February 2010 [1], prices are shown in Table 2.1. And insurance prices for this year equal to price in the previous year. USDA long term projections released in February 2010 [1] gives total demand of corn and soybean for the US. Iowa contributes to about 16% corn production and 13% soybean production in the past few years. Therefore, the projected corn and soybean demand for Iowa can be 16% and 13% [5] of the USDA projection for the US as Table 2.2. Iowa corn and soybean county yields [6] are referred. The state average yields from 2005 to 2013 are used. The corn yield is 168 bushel per acre and the soybean yield is 50 bushel per acre. The cost of planting corn and soybean comes from [7] is shown in Table 2.3.

Table 2.1 USDA projected corn and soybean prices from 2016 to 2020 [1]

year	corn ($/bu)	soybean ($/bu)
2016	3.7	9.25
2017	3.7	9.25
2018	3.7	9.25
2019	3.65	9.20
2020	3.65	9.20

Table 2.2 Corn and soybean demands from 2016 to 2020 in Iowa

year	corn (1000 bu)	soybean (1000 bu)
2016	2,254,400	438,490
2017	2,276,000	442,520
2018	2,297,600	446,420
2019	2,318,400	450,450
2020	2,340,000	454,480

Table 2.3 Cost for corn and soybean yield in Iowa [2]

crop	preharvest cost ($/acre)	harvest cost ($/bu)
corn following corn	468.66	0.386
corn following soybean	415.40	0.386
soybean	263.30	0.126

The available land for corn and soybean in 2013 and 2014 for Iowa is 23,240,000 acres in [5]. We use 23,240,000 acres as land availability for 5 years and $300/acre as the switchgrass contract price.

2.3.2 Results

In this case study, we test the optimization model for land allocation between bioenergy crops and grain crops. The land allocation results are in Table 2.4.

Table 2.4 Land allocation for corn, soybean and switchgrass from 2016 to 2020

year	corn (1000 acres)	soybean (1000 acres)	switchgrass (1000 acres)
2016	13,419	9,599	222
2017	13,547	9,470	222
2018	13,676	9,341	222
2019	13,800	9,218	222
2020	13,928	9,089	222

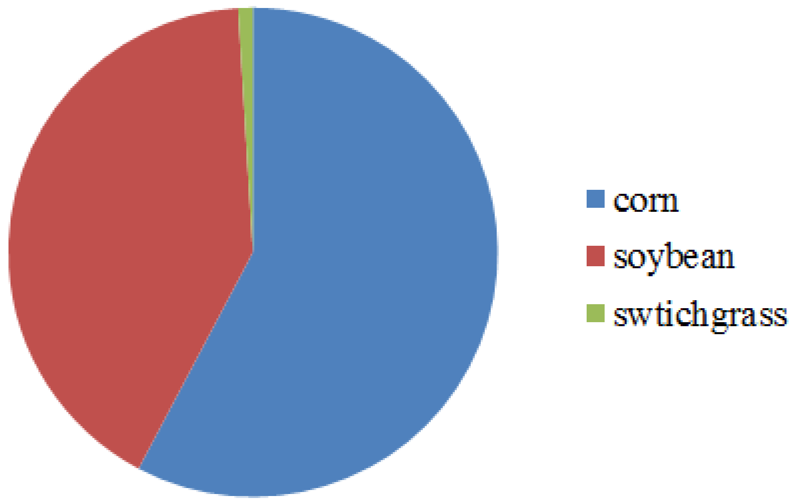

Figure 2.1 Land allocation for corn, soybean and switchgrass with switchgrass price $300/acre in 2016

From Figure 2.1, we can see that corn covers the majority of available land. Acreage assigned to soybean is comparable with that to corn. Acreage for switchgrass is an extremely small piece of land compared to corn and soybean. There are two main reasons that switchgrass only accounts for a negligible proportion of total land: contract price is not attractive enough and farmers must meet the market demands for corn and soybean. Since the market demands for corn and soybean must be satisfied in this land allocation model, farmers are pushed to allocate a large certain piece land for corn and soybean. Government can reduce the market demands for corn and soybean and increase bioenergy crop demands to promote bioenergy crops. In addition, this contract price is relatively high thus leading farmers to turn to switchgrass after fulfilling corn and soybean demands. The switchgrass contract price plays an important role in land allocation. We can change the switchgrass contract price to analyze its impact on land allocation. The land acreage assigned to switchgrass is shown in Table 2.5.

It can be seen that when switchgrass is under $235/acre, switchgrass will not be chosen. But if switchgrass contract price is beyond $235/acre, land acreage switchgrass is estimated to be 221,830 acres. Even when switchgrass price is far more higher than this contract price, farmers still contribute to the same acreage. Hence, $235/acre can be the threshold price for farmers to

Table 2.5 Switchgrass acreage with contract price in Iowa

contract price ($/acre)	switchgrass (1000 acres)
0-235	0
235-500	221.83

take switchgrass into account. Bioenergy companies can refer to the threshold price when they negotiate with farmers. However, in reality, land acreage assigned to bioenergy crops increases with the increasing of the switchgrass contract price. It's possible that when switchgrass price is under $235/acre, some farmers still choose switchgrass. The reason is that farmers are not only profit-oriented as four farmers' identities show. There can be multiple goals and other constraints for farmers, which result in switchgrass, corn and soybean combinations.

2.4 Conclusions

In this chapter, we develop an optimization model for bioenergy crop and grain crop land allocation. This model optimizes productivist farmers' decision making process who pursue only profitability goal. This model considers the crop rotation as the constraint and the demand constraint for a centralized farmer. A case study for Iowa is implemented. Results are given based on realistic projections. Switchgrass contract threshold price is found to be referred for productivist farmers county or state. Meanwhile, bioenergy plants can refer to the threshold price for switchgrass and adjust their supply chains.

We will include uncertainty in our future work. In this optimization model for land allocation between bioenergy crops and grain crops, uncertainty of grain crop prices, yields and market demand for grain crops are not considered. The uncertainty will make the decision making process for farmers more complicated. Market demands for grain crops pull farmers to select grain crops by letting farmers achieve profits. However, market demands for grain crops are influenced by many factors such as global population and development of industrial use of grain crops. The demand uncertainty will also have an effect on farmers' land allocation of grain crops and bioenergy crops. The uncertainty of grain crop prices, yields and demands is to be considered in the future. Reasonable suggestions will be yielded to help farmers make a land allocation between bioenergy crops and grain crops. Information about bioenergy crop threshold prices will be given to both farmers and bioenergy producers to improve their supply chains.

CHAPTER 3. AN OPTIMIZATION MODEL FOR IDENTIFYING THE MOST VULNERABLE LINKS IN A TRANSPORTATION NETWORK

In this chapter, a mixed integer linear programming model for identifying most vulnerable links in a transportation network is proposed. Section 3.1 gives an introduction of identifying most vulnerable links in a transportation network and Section 3.2 introduces the notations. Section 3.3 introduces user equilibrium traffic assignment conditions. Section 3.4 develops a mixed integer linear model for identifying most vulnerable links in a transportation network. In Section 3.5, a case study is implemented.

3.1 Introduction

Transportation network is a kind of infrastructure facility that permits vehicles or other commodities to move. Roads, highways and railways are typical transportation networks. There are various indicators to describe the performance of transportation network. Among those indicators, transportation network vulnerability has attracted an increasing attention of researchers. Network vulnerability demonstrates the consequence of network failures. No matter the failures of transportation network are man-made results like the September 11th attacks on World Trade Center or natural disasters such as blizzard, the transportation system should have the ability to face up to the disruptions thus protecting the safety of users and minimizing the impact of events. System travel time as the generalized travel cost, can demonstrate the consequences of a reduced network. Therefore, system travel time can be used to assess the vulnerability of a transportation network if monetary expenses are not included in the generalized travel cost. Compared to the original network, the more system travel time, the more vulnerable a reduced network is. There is limited quantitative work on transportation network vulnerability assessment. Srinivasan [29] proposed the perspective to identify factors affecting link-level vulnerability. Link capacity is the major characteristic of transportation network. Link capacity reduction can be used to define failures. The transportation system vulnerability must be assessed first to give an account of the network performance if link failures happen. Those links, which are interdicted by a certain budget of capacity reduction and result in the biggest system travel time, are most vulnerable links.

A transportation network vulnerability identification problem is a bilevel programming problem. An attacker aims at maximizing the system travel time to disrupt the transportation network at the upper level. However, at the lower level, the transportation system makes an optimal traffic assignment based on deterministic user equilibrium to simulate users' travel through the system. The problem is how to analyze system travel time of a transportation network. Given a transportation network, the system travel time is relative to traffic assignment. Traffic assignment problem concerns with the traffic flow pattern in routes between origins and destinations. Wardrop's first principle states that the travel time in all routes are equal and less than those which would be experienced by a single user on any unused route. This principle gives an intuitive equilibrium for transportation a network that users all travel with the shortest travel time route. For approximately six decades, Beckmann's [9] formulation of Wardrop's first principle of static traffic assignment has been applied to various traffic assignment problems. Therefore, static traffic assignment problem can be represented using Beckmann's formulation and system travel time can be yielded from the traffic assignment.

Under a certain capacity reduction budget, there are infinite combinations of link failures and infinite reduced networks. It's difficult to identify the most vulnerable links whose failures result in the biggest system travel time through numerous choices. An optimization for identifying most vulnerable links for a transportation network is needed. If the most vulnerable links' capacities are reduced, the reduced network will experience the biggest system travel time. Therefore, the objective function of the model is system travel time. All links in the network can fail under a total capacity reduction. The traffic assignment problem can be represent by a set of constraints. CPLEX can be used to solve the optimization problem.

3.2 Notations

Sets

- $\mathbb{A}$: set of links.
- $\mathbb{W}$: set of origin-destination (OD) pairs.
- $\mathbb{R}_w$: set of routes for OD pair $w \in \mathbb{W}$.

Parameters

- q^w: fixed OD demands for the OD pair w.
- δ_{ap}^w: if $\delta_{ap}^w = 1$, route p between OD pair w uses link a and $\delta_{ap}^w = 0$ otherwise.
- y_a: capacity for link a.
- $\Delta\bar{y}_a$: the upper bound of capacity reduction for link a.
- T_a: travel time function parameter for link a.
- R_a: travel time function parameter for link a.
- b: attacker's budget for total capacity reduction.
- M: an extremely big positive number.
- $\beta_a^0, \beta_a^1, \beta_a^2$: regression coefficients of travel time function for link a.

Decision Variables

- Δy_a: capacity reduction for link a.
- x_a: traffic flow for link a.
- t_a: travel time for link a.
- f_p^w: traffic flow of route p for OD pair w.
- c_p^w: travel time of route p for OD pair w.
- π^w: the shortest travel time for OD pairs w.

Function

- $t(x_a, y_a) = T_a[1 + R_a(\frac{x_a}{y_a})^4]$: travel time function for link a that relates to link traffic flow and link capacity.

3.3 User Equilibrium Traffic Assignment Conditions

Given a network whose link capacity is y_a, the user equilibrium traffic assignment conditions can be stated as [24]:

$$\sum_{p=1}^{R_w} f_p^w = q^w, \forall w \in \mathbb{W} \tag{3.1}$$

$$x_a = \sum_{w=1}^{W} \sum_{p=1}^{R_w} \delta_{ap}^w f_p^w, \forall a \in \mathbb{A} \tag{3.2}$$

$$c_p^w = \sum_{a=1}^{A} \delta_{ap}^w t_a, \forall w \in \mathbb{W}, \forall p \in \mathbb{R}_w \tag{3.3}$$

$$0 \leq f_p^w \perp (c_p^w - \pi^w) \geq 0, \forall w \in \mathbb{W}, \forall p \in \mathbb{R}_w \tag{3.4}$$

$$t_a = T_a[1 + R_a(\tfrac{x_a}{y_a})^4], \forall a \in \mathbb{A} \tag{3.5}$$

$$x_a \geq 0, t_a \geq T_a, \forall a \in \mathbb{A} \tag{3.6}$$

$$\pi^w \geq 0, \forall w \in \mathbb{W}. \tag{3.7}$$

In user equilibrium traffic assignment conditions, the traffic flow x_a should satisfy (3.1)-(3.7). Equation (3.1) indicates that for each origin and destination pair, the demand is satisfied by the sum of flow for each route. (3.2) means that the flow on a link equals to all routes flow that pass this link. (3.3) demonstrates the travel time for each route equals to the sum of link travel time that the route includes. The complimentary constraints in (3.4) requires that for an origin destination pair, traffic flow is all assigned to any route with the shortest travel time. Those routes whose travel time is larger than the shortest route travel time, don't have traffic flow. So, it's either that a route's flow equals to 0 or that a route's travel time equals to the shortest route travel time. In (3.5), the link travel time function is used. Equation (3.6)-(3.7) state that all variables including traffic flow and traffic time in the conditions are greater than zero.

3.4 Identifying The Most Vulnerable Links In A Transportation Network

The model only introduces generalized travel cost as the judgement for vulnerability. The more increase of generalized travel cost for a reduced network is compared to original network, the more vulnerable the reduced network is. Since the generalized travel cost of original network is fixed, the increase of generalized travel cost for reduced network is consistent with generalized travel cost for reduced network. Concretely, the bigger generalized travel cost for reduced network is, the more vulnerable the failure links are. Besides, the model makes the assumption that no monetary expenses are included in the generalized travel cost. So, the vulnerability is demonstrated by system travel time. In situations that no tolls are in the transportation network, monetary expenses are unnecessarily considered. No tolls for road network or highway network are common around states. System travel time equals the sum of travel time for each link. The most vulnerable reduced transportation network system maximizes the system travel time. That is: the worst link failures consequence under certain budget of link capacity reduction. This model doesn't cope with the discrete link failure but consider the continuous link capacity reduction. The flow assignment problem can use Wardrop's first principle to illustrate user equilibrium.

$$\max_{\Delta y,x,f,t,\pi,c} \quad Q^\top \pi \tag{3.8}$$

$$\text{s. t.} \quad \sum_{a=1}^{A} \Delta y_a \leq b \tag{3.9}$$

$$\sum_{p=1}^{R_w} f_p^w = q^w, \forall w \in \mathbb{W} \tag{3.10}$$

$$x_a = \sum_{w=1}^{W} \sum_{p=1}^{R_w} \delta_{ap}^w f_p^w, \forall a \in \mathbb{A} \tag{3.11}$$

$$c_p^w = \sum_{a=1}^{A} \delta_{ap}^w t_a, \forall w \in \mathbb{W}, \forall p \in \mathbb{R}_w \tag{3.12}$$

$$0 \leq f_p^w \perp (c_p^w - \pi^w) \geq 0, \forall w \in \mathbb{W}, \forall p \in \mathbb{R}_w \tag{3.13}$$

$$t_a = T_a[1 + R_a(\tfrac{x_a}{y_a - \Delta y_a})^4], \forall a \in \mathbb{A} \tag{3.14}$$

$$x_a \geq 0, t_a \geq T_a, \forall a \in \mathbb{A} \tag{3.15}$$

$$\pi^w \geq 0, \forall w \in \mathbb{W} \tag{3.16}$$

$$0 \leq \Delta y_a \leq \Delta \bar{y}_a, \forall a \in \mathbb{A}. \tag{3.17}$$

The objective of the model is to maximize the system travel time (3.8). Wardrop's first principle states that the travel time in all routes are equal and less than those which would be experienced by a single user on any unused route. Objective function (3.8) uses the principle to simply the system travel time. The travel time for each origin and destination pair equals to the shortest route travel time for that origin and destination pair. The system travel time equals the sum of travel time for each origin and destination pair. Constraint (3.9) requires certain budget that can cause link failures. Constraint (3.10)-(3.16) are user equilibrium traffic assignment conditions according to constraints (3.1)-(3.7). Constraint (3.17) requires nonnegative link capacity reduction variables.

The nonlinear (3.13) and travel time function (3.14) can be linearized. Therefore, the model (3.8)-(3.17) can be reformulated as follows.

$$\max_{\Delta y, x, f, t, \pi, c} \quad Q^\top \pi \tag{3.18}$$

$$\text{s.t.} \quad \sum_{a=1}^{A} \Delta y_a \leq b \tag{3.19}$$

$$\sum_{p=1}^{R_w} f_p^w = q^w, \forall w \in \mathbb{W} \tag{3.20}$$

$$x_a = \sum_{w=1}^{W} \sum_{p=1}^{R_w} \delta_{ap}^w f_p^w, \forall a \in \mathbb{A} \tag{3.21}$$

$$c_p^w = \sum_{a=1}^{A} \delta_{ap}^w t_a, \forall w \in \mathbb{W}, \forall p \in \mathbb{R}_w \tag{3.22}$$

$$c_p^w - \pi^w \geq 0, \forall w \in \mathbb{W}, \forall w \in \mathbb{W}, \forall p \in \mathbb{R}_w \tag{3.23}$$

$$f_p^w \geq 0, \forall w \in \mathbb{W}, \forall p \in \mathbb{R}_w \tag{3.24}$$

$$c_p^w - \pi^w \leq \theta_p^w M, \forall w \in \mathbb{W}, \forall p \in \mathbb{R}_w \tag{3.25}$$

$$f_p^w \leq (1 - \theta_p^w) M, \forall w \in \mathbb{W}, \forall p \in \mathbb{R}_w \tag{3.26}$$

$$\theta_p^w \text{ binary}, \forall w \in \mathbb{W}, \forall p \in \mathbb{R}_w \tag{3.27}$$

$$t_a = \beta_a^0 + \beta_a^1 x_a + \beta_a^2 \Delta y_a, \forall a \in \mathbb{A} \tag{3.28}$$

$$x_a \geq 0, 0 \leq \Delta y_a \leq \Delta \bar{y}_a, t_a \geq T_a, \forall a \in \mathbb{A} \tag{3.29}$$

$$\pi^w \geq 0, \forall w \in \mathbb{W}. \tag{3.30}$$

Hu [18] proposed a method to transform the complementary constraint to a mixed integer linear constraint by an extremely large parameter. The big-M method can be well applied to (3.4). Constraints (3.23)-(3.27) are based on [18] transformation. For (3.14), methodologies such as piece-wise linearization can be applied to deal with those kinds of nonlinear term. But most of the methodologies require huge computation efforts. Considering the continuity of the link capacity reduction, the travel time function can be approximated by a linear function using linear regression. Numbers of travel time data with flow and link capacity reduction are generated for each link. Then, a linear regression is performed to yield (3.28). But the problem is that linear regression for travel time function cannot guarantee $t_a \geq T_a$ in (3.16). Two pieces of the travel time function are utilized to accomplish reasonable linear approximation as (3.31) shows. Eventually, a mixed integer linear model for identifying the most vulnerable links is built.

$$t_a = \max\{\beta_a^0 + \beta_a^1 x_a + \beta_a^2 \Delta y_a, T_a\}, \forall a \in \mathbb{A}. \tag{3.31}$$

Constraints (3.42)-(3.45) are equivalent to (3.31) under $t_a \geq T_a$ in (3.16). θ_a is a binary variable. If $\theta_a = 1$, $\beta_a^0 + \beta_a^1 x_a + \beta_a^2 \Delta y_a \geq T_a$ in (3.42) then $t_a = \beta_0 + \beta_1 x_a + \beta_2 \Delta y_a$ based on (3.44). Otherwise, t_a will be pushed to be equal to T_a. So the complete mixed integer linear formulation is as follows.

$$\max_{\Delta y, x, f, t, \pi, c} \quad Q^{\top}\pi \tag{3.32}$$

$$\text{s. t.} \quad \sum_{a=1}^{A} \Delta y_a \leq b \tag{3.33}$$

$$\sum_{p=1}^{R_w} f_p^w = q^w, \forall w \in \mathbb{W} \tag{3.34}$$

$$x_a = \sum_{w=1}^{W} \sum_{p=1}^{R_w} \delta_{ap}^w f_p^w, \forall a \in \mathbb{A} \tag{3.35}$$

$$c_p^w = \sum_{a=1}^{A} \delta_{ap}^w t_a, \forall w \in \mathbb{W}, \forall p \in \mathbb{R}_w \tag{3.36}$$

$$c_p^w - \pi^w \geq 0, \forall w \in \mathbb{W}, \forall p \in \mathbb{R}_w \tag{3.37}$$

$$f_p^w \geq 0, \forall w \in \mathbb{W}, \forall p \in \mathbb{R}_w \tag{3.38}$$

$$c_p^w - \pi^w \leq \theta_p^w M, \forall w \in \mathbb{W}, \forall p \in \mathbb{R}_w \tag{3.39}$$

$$f_p^w \leq (1 - \theta_p^w) M, \forall w \in \mathbb{W}, \forall p \in \mathbb{R}_w \tag{3.40}$$

$$\theta_p^w \text{ binary}, \forall w \in \mathbb{W}, p \in \mathbb{R}_w \tag{3.41}$$

$$\beta_a^0 + \beta_a^1 x_a + \beta_a^2 \Delta y_a \geq -(1 - \theta_a) M + T_a, \forall a \in \mathbb{A} \tag{3.42}$$

$$T_a \geq -\theta_a M + \beta_a^0 + \beta_a^1 x_a + \beta_a^2 \Delta y_a, \forall a \in \mathbb{A} \tag{3.43}$$

$$\beta_a^0 + \beta_a^1 x_a + \beta_a^2 \Delta y_a \leq t_a \leq M(1 - \theta_a) + \beta_a^0 + \beta_a^1 x_a + \beta_a^2 \Delta y_a, \forall a \in \mathbb{A} \tag{3.44}$$

$$t_a \leq M\theta_a + T_a, \forall a \in \mathbb{A} \tag{3.45}$$

$$x_a \geq 0, 0 \leq \Delta y_a \leq \Delta \bar{y}_a, t_a \geq T_a, \theta_a \text{ binary}, \forall a \in \mathbb{A} \tag{3.46}$$

$$\pi^w \geq 0, \forall w \in \mathbb{W}. \tag{3.47}$$

3.5 Case Study

3.5.1 Data

To evaluate the performance of the proposed mixed integer linear model for identifying the most vulnerable links in a transportation network vulnerability, a network example in [30] is used. Figure 3.1 is the test network. In this case, there are six nodes and sixteen links. But only two pairs of origin and destination are in this network. Nodes 1 and 6 are origins and destinations. The travel demand for this network varies from scenario to scenario as shown in

Table 3.1. The network parameters including link capacities, and travel time parameters T_a and R_a are in Table 3.2.

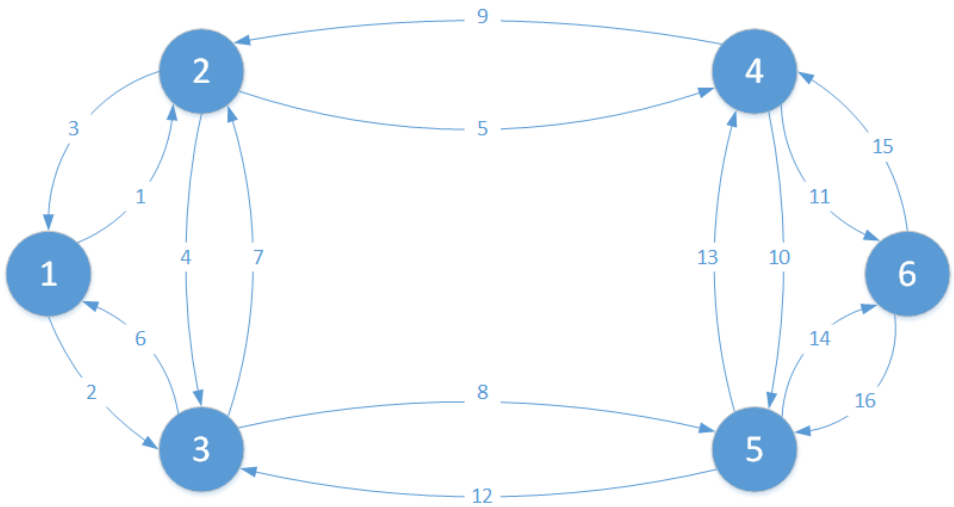

Figure 3.1 Test network

Table 3.1 Traffic demand scenarios

scenario	demand from 1 to 6	demand from 6 to 1	total demand
1	5	10	15
2	10	20	30

Table 3.2 Parameters of the test network

link	link capacity	T_a	R_a
1	3	1	10
2	10	2	2.5
3	9	3	1
4	4	4	5
5	3	5	10
6	2	2	10
7	1	1	10
8	10	1	1
9	45	2	4
10	3	3	1
11	2	9	0.22
12	6	4	2.5
13	44	4	6.25
14	20	2	16.5
15	1	5	1
16	4.5	6	0.17

The travel time function for each link is analyzed to give intuitive recognition of the nonlinear term. For example, travel time function (3.14) for link 1 is plotted with traffic flow and link capacity reduction. Travel time increases with the increasing of traffic flow and link capacity reduction. It can be seen that with the link capacity reduction approximating the original link capacity, the travel time jump to an extremely large link travel time. If the capacity reduction for link 1 is not very close to the original link capacity, the travel time function is very flat in Figure 3.2. Linear approximation can be used to approximate the nonlinear link travel time function.

Then linear regression is used to approximate the nonlinear travel time function. Randomly generate 10,000 points of traffic flow and capacity reduction for each link. Calculate the travel time for the 10,000 points based on the nonlinear travel time function. Travel time is used as response while traffic flow and link capacity reduction are explanatory variables. Linear regression is performed using the 10,000 experiment points. Then the linear relationship (3.29) is formed. All linear regression coefficients for sixteen links $\beta_a^0, \beta_a^1, \beta_a^2$ are in Table 3.3.

Table 3.3 Linear regression coefficients of the test network

link	β_0	β_1	β_2
1	-1.58×10^2	5.59×10	1.21×10^2
2	1.37	0.23	0.15
3	–6.07	1.63	2.30
4	-7.97×10^3	9.43×10^2	4.54×10^3
5	-6.36×10^3	7.51×10^3	4.80×10^4
6	-2.62×10^4	4.57×10^3	3.02×10^4
7	-1.03×10^6	1.22×10^5	2.35×10^6
8	–9.27	1.21	2.33
9	1.80	0.02	0.01
10	-3.71×10^3	4.40×10^2	2.81×10^3
11	-1.49×10^2	5.61×10	1.80×10^2
12	-8.13×10^2	9.58×10	3.11×10^2
13	3.30	0.08	0.04
14	1.74	0.09	0.03
15	-9.95×10^4	1.79×10^4	2.25×10^5
16	-4.27×10	8.63	2.45×10

Travel time function using linear regression is plotted. Linear regression approximation for travel time of link 1 demonstrates pretty similar trend to the nonlinear travel time function. Considering $t_a \geq T_a$, the travel time function are approximated by two pieces. Figure 3.3 can well approximate Figure 3.2.

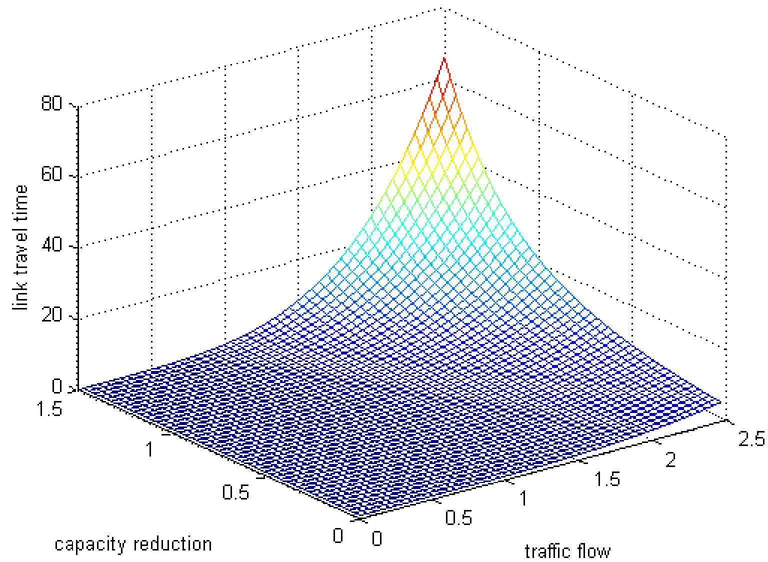

Figure 3.2 Travel time function for link 1 within half capacity reduction

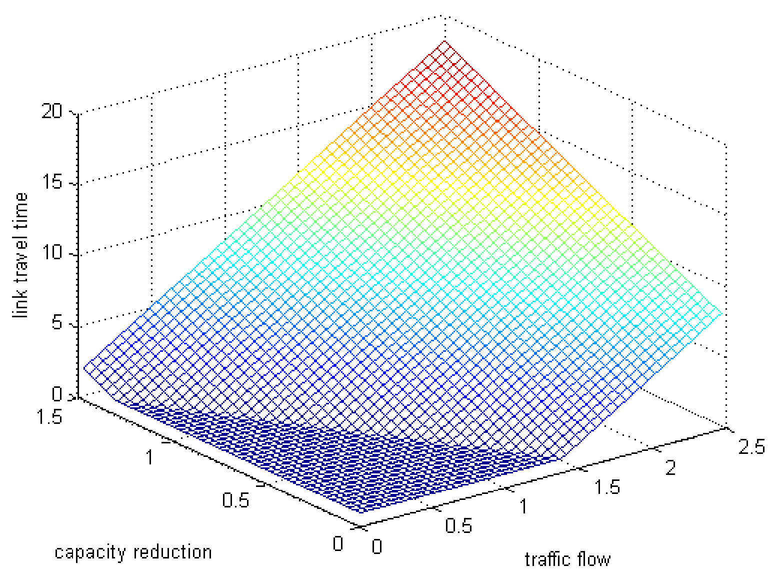

Figure 3.3 Travel time function for link 1 with two linear pieces

All data for the test case are available according to model (3.32)-(3.46). Given a certain budget of total capacity reduction b, the vulnerability of the network is demonstrated by the increase of objective function. Those links assigned link capacity reduction are most vulnerable links.

3.5.2 Results

In this case study, we test the mixed integer linear model for identifying most vulnerable links in a transportation network. The model is solved in CPLEX/AMPL. Computation experiments are executed on a laptop with Intel Core (TM) i5-3230M 2.60 GHz CPU and 4 GB RAM.

Given the budget of capacity reduction $b = 0.5$, the optimal solution is: $\Delta y_{15} = 0.44, \Delta y_{16} = 0.06$, for demand scenario 1. The vulnerable links are 15 and 16 because the capacity reduction of links 15 and 16 leads to the maximum system travel time. Compared to the network without failures in Table 3.4, the system travel time increases by 59%. That means links 15 and 16 are very vulnerable. Once links 15 and 16 are interdicted, the system accessibility will suffer a lot causing long system travel time. The result is reasonable based on the traffic flow assignment when the network is not interdicted. Without network link failures, link 15 plays an important role to move vehicles for its big traffic flow assignment. If link 15 fails and its capacity is heavily reduced, vehicles have to move through other links. There is no traffic flow assigned to link 4 with the original network. Therefore, link 4 failure will not result in huge impact on system travel time and it's not a vulnerable link.

Table 3.4 Most vulnerable links with capacity reduction budget $b = 0.5$ for scenario 1

link	link capacity reduction Δy_a	traffic flow x_a without capacity reduction	traffic flow x_a with capacity reduction
1	0	5	2.95
2	0	0	2.05
3	0	0	1.42
4	0	0	0
5	0	5	5
6	0	10	8.58
7	0	0	2.05
8	0	0	0
9	0	0	1.42
10	0	8.85	2.18
11	0	0	2.82
12	0	10	8.58
13	0	0	1.42
14	0	5	2.18
15	0.44	3.85	0
16	0.06	6.15	10
system travel time		773	1,232

The maximum system travel time increases as network capacity reduction increases in Figure 3.4 and the vulnerable links are shown in Table 3.5. In the most vulnerable case, 0.7% of the total capacity reduction can double the total system travel time. The total system travel time increases more quickly when capacity reduction is under 0.6 than beyond 0.6.

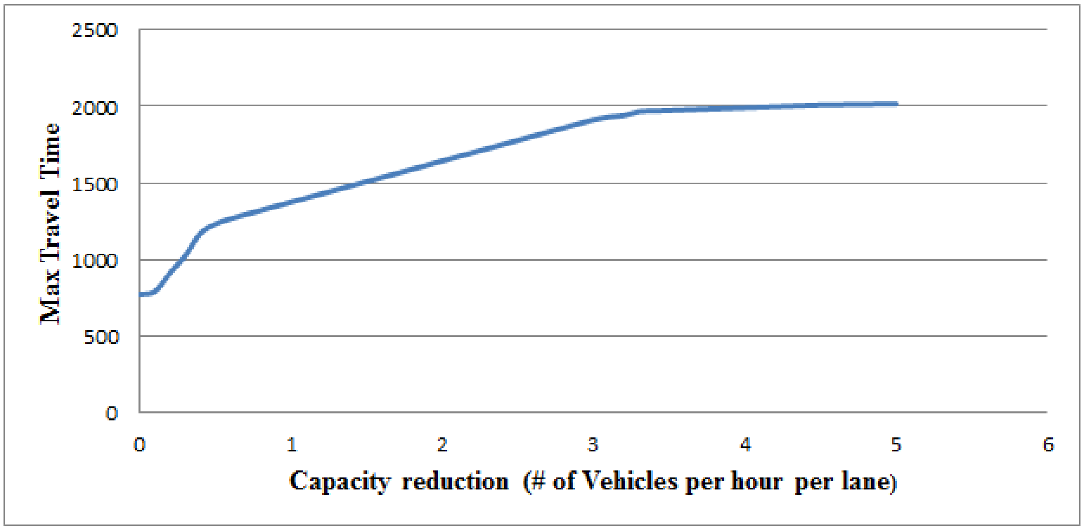

Figure 3.4 Maximum system travel time with different capacity reductions with scenario 1

Table 3.5 Most vulnerable links with different capacity reductions with scenario 1

capacity reduction budget b	most vulnerable links
0.1-0.4	15
0.5	15,16
0.6-3.3	7,15,16
3.4-4.7	1,5,7,15,16
4.8-5.0	1,6,7,15,16

For demand scenario 2, the results are similar to the results of demand scenario 1. Given the budget of capacity reduction $b = 0.5$, the optimal solution is still: $\Delta y_{15} = 0.44, \Delta y_{16} = 0.06$, for demand scenario 2. The vulnerable links are 15 and 16 because the capacity reduction of links 15 and 16 leads to the maximum system travel time. Compared to the network without failures in Table 3.4, the system travel time increases by 36%. That means links 15 and 16 are vulnerable. Once links 15 and 16 are interdicted, the transportation system perform worst than network without failures. The result is reasonable based on the traffic flow assignment when the network is not interdicted. Without network link failures, link 15 move some vehicles in the system. If link 15 fails and its capacity is heavily reduced, vehicles have to move through other links. There is no traffic flow assigned to link 4 with the original network. Therefore, link 4 failure will not result in huge impact on system travel time and it's not a vulnerable link.

Table 3.6 Most vulnerable links with capacity reduction budget $b = 0.5$ for scenario 2

link	link capacity reduction Δy_a	traffic flow x_a without capacity reduction	traffic flow x_a with capacity reduction
1	0	8.48	8.48
2	0	1.52	1.52
3	0	14.26	14.27
4	0	0	0
5	0	8.48	8.48
6	0	5.74	5.73
7	0	8.42	8.42
8	0	1.52	1.52
9	0	5.85	5.85
10	0	0	0
11	0	8.48	8.48
12	0	14.15	14.15
13	0	0.29	5.85
14	0	1.52	1.52
15	0.44	5.56	0
16	0.06	14.44	20
system travel time		2,773	3,775

The maximum system travel time increases as network capacity reduction increases in Figure 3.5 and the vulnerable links are shown in Table 3.7. In the most vulnerable case, 2.8% of the total capacity reduction can double the total system travel time. The total system travel time increases more quickly when capacity reduction is under 0.6 than beyond 0.6.

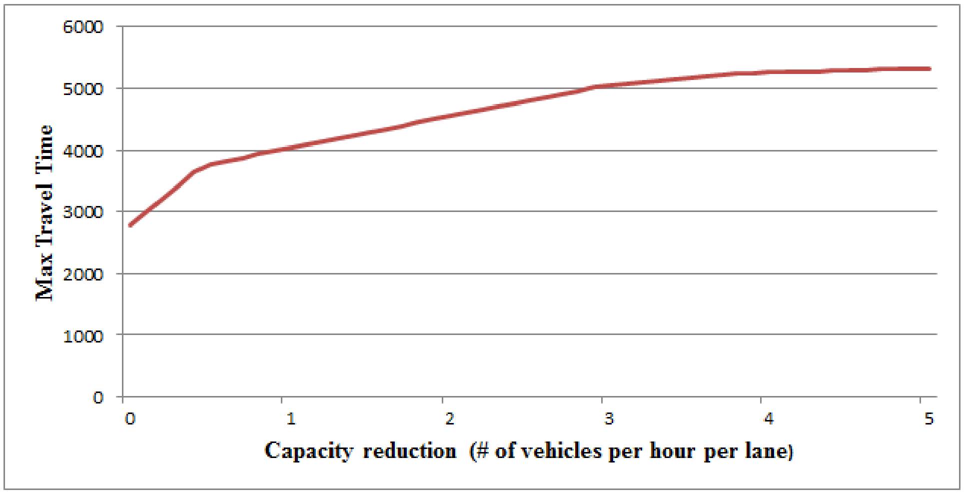

Figure 3.5 Maximum system travel time with different capacity reductions with scenario 2

Table 3.7 Most vulnerable links with different capacity reductions with scenario 2

capacity reduction budget b	most vulnerable links
0.1-0.4	15
0.5-2.9	15,16
3.0-3.8	6,15,16
3.9-5.0	3,6,15,16

We compared the results of two demand scenarios. It's found that link 7 becomes less vulnerable when network demand increases under certain capacity reduction budget. When the transportation network becomes busier, the final channel – links 15 and 16 are more significant. A small quantity of capacity reduction on links 15 or 16 results in tremendous failure of the system. As network demand increasing, the importance of other links cannot be compared to the importance of links 15 and 16. That is the reason why link 7 becomes less vulnerable when network demand increases while links 15 and 16 are still vital to the network.

3.6 Conclusions

In this chapter, we developed an optimization model for identifying most vulnerable links in a transportation network. To deal with the complementary constraints in this model, we implemented the big-M method to convert the nonlinear constraint to mixed integer linear constraint. For simplification of the nonlinear travel time function, linear regression is used to approximate the relationship among link travel time, traffic flow and link capacity reduction. Finally, a mixed integer linear model is developed.

In the case study, we considered two demand scenarios and implemented the model according to different scenarios. The results of two scenarios are compared and explained. Even a small amount of capacity reduction for a network will lead to a great increase of system travel time in the most vulnerable case. It's found that there is a great possibility that the vulnerable network links are from those links undertaking large traffic flows without network failure. Besides, with the increasing of network demand, links as the first or the last channels seem more vulnerable than those in the middle of the network.

We will address the traffic demand uncertainty in this model. The traffic demand has impact on the vulnerability of the network and the most vulnerable links identification aspect. Considered the demand uncertainty, vulnerability for transportation network will be assessed and vulnerable links will be identified to give more reliable information of the network. Most continuous network design models aims at minimizing the system travel time given a budget. However, building transportation networks which have the ability to conquer failures brought by disasters or man-made attacks becomes increasingly important. Based on the optimization model for identifying most vulnerable links in a transportation network, continuous network design problem will be formulated in a new perspective to build resilient infrastructures.

CHAPTER 4. DISCUSSION

4.1 Contributions

In Chapter 2, we develop an optimization model for bioenergy crop and grain crop allocation. This model quantifies a centralized productivist farmer's decision making process. Farmers can optimize their goals by making a land allocation for grain crops and bioenergy crops. The objective of this optimization model is to maximize the profit that the farmer can make during the planning horizon. Gain crop prices, yields, costs and bioenergy crop contract prices are included in the objective function. Besides, crop rotations which are agriculturally proved as practical management approaches serve as constraints in the objective model. S-ince this model is for a centralized farmer who represents a large group of farmers, demand constraints are included. The model is proposed to make the optimal land allocation between bioenergy crops and grain crops for farmers. And this model is used to analyze bioenergy crop contract price impact on the land acreage assigned to bioenergy crop for farmers. On the other hand, the model can be used to estimate land acreage assigned to bioenergy crop for bioenergy producer and help bioenergy producers to determine whether to modify bioenergy crop contract price. In the case study, a case study of Iowa is conduct. Results are given based on realistic projections. Switchgrass contract threshold price is found to be referred for productivist farmers county or state. Meanwhile, bioenergy plants can refer to the threshold price for switchgrass and adjust their supply chains.

In Chapter 3, a mixed integer linear model for identifying most vulnerable links in a transportation network is formulated. The vulnerability of a transportation network is demonstrated by the increase of system travel time. When network failure happens, namely the link capacities in the network are reduced. The interdicted network still undertakes traffic demand and can reach new equilibrium for traffic flow assignment. Under certain capacity reduction budget, the vulnerable links are links which result in the maximum system travel time if they fail. The transportation vulnerability identification model maximizes the system travel time given certain capacity reduction budget. And Wardrop's first principle is used to make traffic flow assignment in this model. A single level nonlinear model with complementary constraints and nonlinear travel time is built firstly. The big-M method is implemented to transform the nonlinear complementary constraints into mixed integer linear constraints. Besides, linear regression is performed to approximate travel time function. Eventually, a mixed integer linear model is developed. The vulnerable links can be identified using this model. In the case study, a sixteen-link network is used to test the performance of the model. Two traffic demand scenario are considered in the case study. And vulnerable links for both demand scenarios are found. And sensitivity analysis of budget of capacity reduction is conduct. As the power of capacity reduction increasing, the more vulnerable this transportation network is. Besides, the most vulnerable links can change with different budget of capacity reduction. For different demand scenario, given the same budget of capacity reduction, the most vulnerable links may different.

4.2 Future Work

In the optimization model for land allocation between bioenergy crops and grain crops that Chapter 2 presents, uncertainty of grain crop prices, yields and market demand for grain crops are not considered. What if the USDA long term projection is not so reliable? Although farmers' insurance help farmers from experience turbulence of grain crop prices and yields, the prices and yields for grain still suffer from variation. Consequently, the grain prices for example corn and soybean price are uncertain in the future. We have no exact idea if the market price of corn is \$3.5/acre or \$4.5/acre. This uncertainty will make the decision making process for farmers more complicated. The grain crop demands have to confront with uncertainty. Market demands for grain crops pull farmers to select grain crops by letting farmers achieve profits. However, market demands for grain crops are influenced by many factors such as global population and development of industrial use of grain crops. The demand uncertainty will also have an effect on farmers' land allocation of grain crops and bioenergy crops. The uncertainty of grain crop prices, yields and demands is to be considered in future work. Reasonable suggestions will be yielded to help farmers make a land allocation between bioenergy crops and grain crops. Information about bioenergy crop threshold prices will be given to both farmers and bioenergy producers to make their supply chains more efficient.

For the transportation network vulnerability identification model, a case study for large and realistic network is to be conduct. The case study in Chapter 3 only has sixteen network links. In order to obtain the more convincing proof of the model performance, more data is to be collected and a large network would be included in the results. In addition, we will address the traffic demand uncertainty in this model. The traffic demand has impact on the vulnerability of the network and the most vulnerable links identification aspect. Considered the demand uncertainty, vulnerability for transportation network will be assessed and vulnerable links will be identified to give more reliable information of the network. Most continuous network design models aims at minimizing the system travel time given a budget. However, building transportation networks which have the ability to conquer failures brought by disasters or man-made attacks becomes increasingly important. Based on the optimization model for identifying most vulnerable links in a transportation network, continuous network design problem will be formulated in a new perspective to build resilient infrastructures.

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