Iowa State University
Digital Repository

2013

Using GIS and intelligent transportation tools for biomass supply chain modeling and cost assessment

Slobodan Gutesa
Iowa State University

Follow this and additional works at: http://lib.dr.iastate.edu/etd

Part of the Agriculture Commons, and the Bioresource and Agricultural Engineering Commons

Recommended Citation

**Using GIS and intelligent transportation tools for
biomass supply chain modeling and cost assessment**

by

Slobodan Gutesa

A thesis submitted to the graduate faculty

In partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

Major: Agricultural Engineering

Program of Study Committee:
Matthew Darr, Major Professor
Konstantina Gkritza
Stuart Birrell

Iowa State University

Ames, Iowa

2013

TABLE OF CONTENTS

ABSTRACT

Stable, functional, and efficient bioethanol production systems on the national level must emphasize solutions of feedstock availability and transportation problems. Transportation logistics are a critical factor in the optimization of biomass supply chains. A single 25 million gallon per year cellulosic ethanol biorefinery will require delivery of 18,500 semi loads of bales to the plant. For a typical corn-stover biomass supply chain, baled corn stover must be transported in two phases, first from the field to a storage site and then from the storage site to the biorefinery. All activities between these two points are interconnected and together they form the biomass supply chain. The goal of supply-chain optimization is to minimize the total cost of these activities (transportation cost per unit, inventory cost per unit etc.) while satisfying the supply demands of a biorefinery.

The objective of the first chapter of this thesis is to provide a detailed report on a recent analysis of production-scale biomass transportation. Specifically, 16,000 large square bales of corn stover were harvested and hauled to satellite storage during the 2011 and 2012 harvest seasons. Intensive Geographic Information Systems (GIS) tracking and video capture of the loading, securement, hauling, and unloading events were collected and the results were summarized.

The second chapter presents specific results including: metrics for measuring supply chain efficiency, current capability of biomass supply chains, and sensitivity analysis to improvements in future supply chains. A discrete modeling technique was utilized to make proper assessment of the supply-chain system performance. The supply-chain model was a representation of a realistic biomass transportation cycle between a single cornfield and biomass

storage. The discrete model included multiple simulations using different model factors. This approach provided complete assessment of influence of various factors on system productivity.

Understanding basic transportation metrics, handling parameters, and their interaction can be crucial for planning and implementing an optimal supply-chain solution. The outcomes of this work can be used to create more efficient supply systems and to improve economic aspects of biofuel production process in general.

CHAPTER 1. GENERAL INTRODUCTION

Stable functional and efficient bioethanol production systems on the national level must place emphasis on feedstock availability and transportation problems. Supply-system logistics refers to all transportation and storage activities that occur in the process of delivering the stover resource from its production location to the location of the biorefinery conversion process. Optimal biomass energy production is directly connected with optimal transportation and supply-chain parameters. Biorefinery feedstock delivery systems usually include large transportation and handling costs. Large financial savings are expected to result from the improvement of such activities.

Previous research has provided detailed examinations of harvesting and baling machinery costs. However, loading and stacking machinery must also be included in research in this area, particularly because this segment of supply-chain machinery has significant impact on overall logistic costs and represents a large potential for optimization and savings.

The first aim of this chapter is to identify specific transportation and handling equipment metrics to properly describe required transportation productivity and associated time windows. The second aim is to collect and summarize all necessary performance metrics. The rationale behind this work is that obtaining relevant machinery performance metrics within a corn-stover supply chain can help provide appropriate background for system optimization. Supply-system improvement can provide significant economic benefits and decrease startup investments. Therefore, detailed machinery performance report can be considered as one of the most important steps in the decision-making process. Expected outcomes of data collection and

visualization will enable development of a data background, essential for development of an industrial-scale feedstock-delivery system for biomass conversion plants. GPS tracking, GIS data processing, and video surveillance will be conducted to collect important performance metrics and parameters. Moreover, discrete-modeling techniques will be introduced to develop an analytical approach for system optimization. Collected data to help examining different supply chain scenarios is an irreplaceable resource for the supply-chain model development. All of the above elements combined will represent a unique decision-making tool that can significantly reduce initial investments and total logistics costs.

Objectives

- Quantify relevant field data to complete corn-stover supply chain modeling in the most accurate fashion. Proposed methods of data collection include field video surveillance, GPS tracking, and GIS data processing. Metrics for evaluation include distribution of operational speeds, distances, and unit cycle times.

- Analyze relationships between factors influencing corn-stover transportation costs. Such factors include transportation demand, number of vehicles per transportation team, bale-handling equipment, and their influence on supply chain productivity.

- Apply relationships between relevant factors on an ExtendSim supply-chain model. Evaluate multiple scenarios and determine an optimal transportation equipment setup, transportation time window, and storage system organization.

Thesis Organization

This thesis contains an introduction, a literature review, two research articles, and a general conclusion. The general introduction includes the objectives of the thesis, a description of the thesis organization, and the author's role in each article.

The second chapter contains a brief literature review and recent findings in the field of biomass production and supply-system organization.

The first article, entitled "Using GIS and Intelligent Transportation Tools for Biomass Transportation Productivity Assessment", describes a scientific application of a Geographic Information System (GIS) and a Global Positioning System (GPS) to collect relevant data.

The second article, "Supply Chain Optimization and Modeling", describes discrete modeling and supply-chain optimization approach. References for each section are included at the end of each chapter.

Authors' Role

The primary author, with the guidance, support, and assistance of co-authors, composed all of the research articles presented in this thesis. Unless otherwise indicated, all procedures were performed by the primary author.

Dr. Matthew Darr conceived the original idea for transportation data collection, spatial analysis and discrete modeling. Dr. Darr also provided continual guidance throughout the result analysis and writing and editing assistance.

CHAPTER 2. REVIEW OF LITERATURE

Bioethanol Production

The biomass production industry is experiencing a rising interest with respect to research and development. Throughout history, plant material has been utilized for a vast variety of applications such as heating, cooking, metallurgy, construction material for buildings, and a great number of transportation methods, fiber sources, medicines, and food and feed (Brown 2013)

However, developed countries have generally abandoned biomass utilization for energy and fuel production in favor of fossil fuel (Demirbas 2009, Brown 2013). Nowadays, in the era of the "carbon economy", humankind satisfies almost all its needs for materials, energy, and chemicals from fossil sources such as coal, petroleum, and natural gas. The current methodology for producing, converting, and consuming energy is not sustainable. Because of the limited amount of fossil fuels and their inefficient exploitation, an increasing need to develop more renewable energy sources has come about. Recently, a more sophisticated approach to biomass exploitation has been developed and simultaneous production of hydrogen, methane, and ethanol has increasingly been utilized to create the possibility of optimizing the bioenergy production life cycle (Piet 2005). According to the Renewable Fuel Standard (RFS) from the Energy Independence and Security Act of 2007, the minimum annual quantity of renewable fuel in the US transportation sector should be increased from 9 billion tons in 2008 to 36 billion in 2022, and after 2016 most renewable fuel must be advanced biofuel derived from cellulosic feedstocks rather than food crops (EISA, 2007). This legislative act has generated intensive research efforts and positioned corn stover as the main focus among available feedstock alternatives. Analysis of a large square-bale corn-stover biomass supply system indicates that, if other agronomic factors

are not in conflict, corn stover can be accessed and supplied to a biorefinery using existing bale-based technologies. Biomass-to-ethanol yield and delivered feedstock cost (including harvest, transportation, and storage activities) are two of the key parameters affecting both the ethanol selling price and the overall viability of bioethanol production (Hamelinck, Hooijdonk et al. 2005). However, the material characteristics of corn stover create certain challenges in terms of supply system design, especially in the area of equipment capacity and efficiency (Hess, Wright et al. 2007).

Biomass Supply-Chain Optimization

Supply system logistics refers to all transportation and storage activities associated with the process of delivering the stover resource from its production location to the conversion process system at the biorefinery. Optimal biomass energy production is directly connected with optimal transportation and supply-chain parameters. Supply-system logistics are one factor that can provide successful and efficient recovery of energy from biomass (Searcy, Flynn et al. 2007). For example, if we consider a single 25 million gallon-per-year cellulosic ethanol biorefinery, at least 18,500 semi loads of corn stover bales must be delivered annually to the plant (Darr and Shah 2012). Finely-adjusted supply-chain parameters are an essential part of efficient exploitation of corn stover, mainly because biomass transportation is followed by several energy and time-consuming activities such as loading, unloading, stacking, and securing (Hess, Wright et al. 2007). Sokhansanj, Kumar et al. (2006) used an integrated biomass-supply analysis and logistics (IBSAL) model to study the delivery of baled biomass. That model recommended decomposition of a single biomass collection area into several satellite storage locations (SSL). Similarly, Morey, D.G et al. (2006) used the "SSL" concept for a study of corn

stover logistics in Minnesota. The cost decrease in this approach is mainly the result of decomposition of a biomass collecting area into several SSL areas with localized transportation. This decentralized system reduces the transportation time window and storage investment compared to a single centralized storage location. An industrial-scale supply chain includes a large number of variables that can take on different values and quite often express a stochastic nature. To effectively deal with those values and their impact on overall supply-chain productivity, simulation might be an adequate method (Lee, Cho et al. 2002). The same author also explained that simulation is an effective tool for dynamically-changing variables and can work for the general optimization of an entire supply chain by finding local optimum values.

A similar concept was recommended by Ingallis (1998). He stated that simulation is an excellent tool for evaluating the effectiveness of certain research scenarios.

REFERENCES

Brown, R. C. (2013). "Biorenewable Resources." (Wiley-Blackwell): 286.

Darr, M. J. and A. Shah (2012). "Biomass storage: an update on industrial solutions for baled biomass feedstocks." Biofuels **3**(3): 321-332.

Demirbas, A. (2009). "Progress and recent trends in biodiesel fuels." Energy Conversion and Management **50**(1): 14-34.

Hamelinck, C. N., et al. (2005). "Ethanol from lignocellulosic biomass: techno-economic performance in short-, middle- and long-term." Biomass and Bioenergy **28**(4): 384-410.

Hess, J. R., et al. (2007). "Cellulosic biomass feedstocks and logistics for ethanol production." Biofuels, Bioproducts and Biorefining **1**(3): 181-190.

Ingallis, R. G. (1998). The value of simulation in modeling supply chains. Simulation Conference Proceedings, 1998. Winter.

Lee, Y. H., et al. (2002). "Supply chain simulation with discrete–continuous combined modeling." Computers & Industrial Engineering **43**(1–2): 375-392.

Morey, R. V., et al. (2006). "Biomass for electricity and process heat at ethanol plants." Applied Engineering in Agriculture: 728.

Piet, N. L. L. (2005). "Biofuels for Fuel Cells: Renewable Energy from Biomass Fermentation.".

Searcy, E., et al. (2007). The Relative Cost of Biomass Energy Transport. Applied Biochemistry and Biotecnology. J. Mielenz, K. T. Klasson, W. Adney and J. McMillan, Humana Press**:** 639-652.

Sokhansanj, S., et al. (2006). "Development and implementation of integrated biomass supply analysis and logistics model (IBSAL)." <u>Biomass and Bioenergy</u> **30**(10): 838-847.

CHAPTER 3. USING GIS AND INTELLIGENT TRANSPORTATION TOOLS FOR BIOMASS TRANSPORTATION PRODUCTIVITY ASSESSMENT

Slobodan Gutesa, Matthew Darr

Abstract

Recently, a great amount of interest has been expressed with respect to techniques for improving transportation industry productivity. Establishment of a transportation process is always followed by large financial expenses resulting from intensive energy use and human labor consumption. By achieving system optimization, i.e., reducing unnecessary capacities from the system, it is possible to accomplish significant financial savings. To conduct efficient and successful productivity evaluation of such industrial systems, an appropriate dataset describing existing conditions must be provided.

Understanding basic transportation metrics, handling parameters, and their interaction can be crucial for planning and implementing an optimal supply chain solution. To obtain these essential parameters, intensive GIS tracking and video capture of the loading, securement, hauling, and unloading events were collected and the results were summarized.

Introduction

The biomass-processing industry in the midwestern United States is expected to enlarge corn-stover feedstock demand in the region. Dupont Cellulosic Ethanol is building a 25 Million Gallon per Year ethanol plant in Story County, Iowa, that will use corn stover as a main feedstock. Some experimental studies indicate that this facility will require around 700,000 bales

of corn stover per year. The goal of supply chain optimization is to minimize the total cost of associated activities such as transportation and storage while satisfying the supply demands of such a bio-processing plant (Darr and Shah 2012).

Developing an effective and timely accurate corn-stover supply chain can produce significant savings and bio-ethanol production benefits (Sokhansanj, Kumar et al. 2006). To address optimization problems it is essential to obtain relevant transportation parameters regarding current system productivity.

Recently, more than 50,000 corn-stover bales were transported to several storage locations in Story County, IA. During this transportation, data was intensively collected. The data collection included GPS vehicle tracking and video surveillance. This data will represent a valuable resource in making a confident assessment of possible corn-stover supply chain solutions.

The Global Positioning System (GPS) found its application to transportation from its earliest beginning. Moreover, the Global Positioning System and the Geographical Information Systems (GIS), working in tandem, provide a powerful tool for spatial analysis (Kenedy 2002). The three GPS components most frequently used in civilian applications are absolute location, relative movement, and time transfer. Peyton (2012) used electronic data-logging of GPS position and CAN messages to collect logistic parameters for a corn-stover supply chain. The data logger provided spatial information that allowed generation of a GIS map. Using a GPS data-logging system along with GIS software it is possible to conduct an accurate assessment of machinery performance by retrieving parameters such as position, time, speed, and fuel consumption.

While recent studies do provide detailed reports on productivity rates for corn-stover collection and handling, very few of them considered road transportation as an element of great potential for savings and optimization. In addition, there is very little data on biomass road transportation. To conduct accurate and realistic transportation modeling it is essential to provide detailed and well-organized input parameters (Appelbaum and Berechman 1991). As one of the most important prerequisites for successful modeling, CMSA-Huntsville (2013) outlined that, in realistic traffic scenarios, the modeled vehicles must behave similarly to real vehicles. To satisfy these conditions, vehicle behavior can be examined using intensive GPS tracking and GIS analytical tools.

Research objective

The research goal of this study is to quantify and report relevant field data to provide input parameters for corn-stover supply chain modeling in the most accurate fashion. Methods of data collection include field video surveillance, GPS tracking, and GIS data processing. Metrics for evaluation will be represented through distribution of operational speeds, unit cycle times, number of delivered truckloads per hour, and many other parameters.

Methods and Materials

Corn stover is typically transported using trucks equipped with 53-ft semi-trailers and cargo units are mainly large square bales. Nowadays, trucks carry about 80% of all freight (measured in tons) and almost every transportation mode is somehow related to a truck trip (New

York Metropolitan Transportation Council, 2003). In a corn-stover supply chain, road vehicles usually pass through six stages (figure 1.)
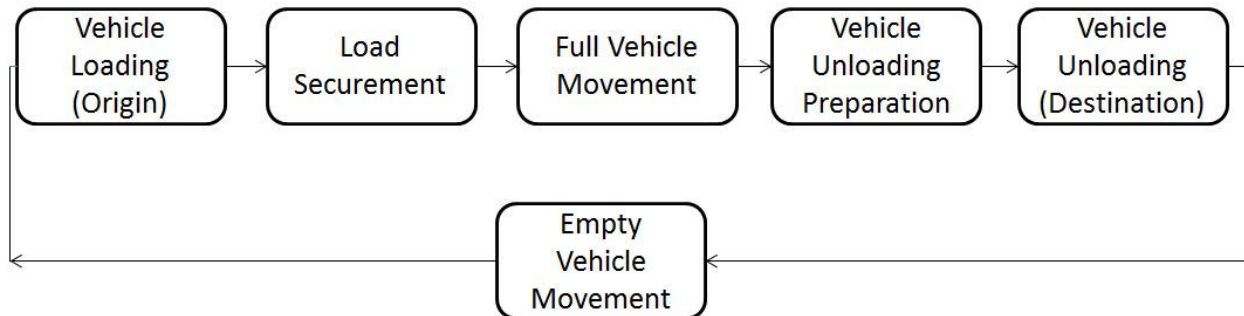

Figure 1. Corn Stover Transportation Stages (Single Transportation Cycle)

According to this figure, it is necessary to describe all vehicle movement stages and to provide data distribution for time at the vehicle loading point, time at the vehicle unloading point, travel time for both full and empty stages, the number of delivered loads per hour, and the average speed for different types of road surfaces (gravel, pavement, highway etc.)

Providing reliable information on the parameters from the above transportation system may represent a valuable resource in supply-chain modeling.

Transportation Origin and Destination

As described earlier, a transportation cycle typically starts at the corn field where biomass bales are loaded onto semi-trailers and transported to one of the industrial-scale biomass storage locations. There are two different types of cellulosic biomass stacks:

1.) *Field-Edge Stack-* Short term, temporary storage where all the bales from a corn field are grouped together to provide a more efficient loading process. Biomass-hauling typically starts at such a location.

2.) ***Industrial-Scale Stack-*** a long-term storage system that represents the origin of the biomass hauling process. There are many types of industrial storage: open storage, tarped storage, permanent structure storage, and anaerobic storage.

Transportation Methods

Corn stover is typically transported using trucks equipped with 53-ft semi-trailers and the cargo units are mainly large square bales. To achieve optimal transportation and storage conditions, corn-stover balers are usually configured to make bales with dimensions 0.91 m high x 1.22 m wide x 2.44 m long.

In addition, on midwest roadways there are four main vehicle platforms used to transport square bales of bio-mass:

1.) Pick-up style light truck and trailer combination

2.) Straight truck

3.) Truck tractor/ semi-trailer combination (usually 53-ft trailers)

4.) Implements of husbandry- a combination of agricultural tractors and wagons.

Table 1 outlines the dimension restrictions for hauling loads on Iowa roadways. These dimensions are the standard legal maximums for both primary and secondary road systems.

	Vehicle Length Restrictions	Load Width Restriction	Load Height Restriction	Approx. Number of Bales Hauled
Pick-up Truck / Trailer	53' Trailer	8'6"	13' 6"	Depends on Size of trailer (20-33)
Pick-up Truck / Trailer *(With annual wide load permit)**	75' Trailer	12'5"	13' 10"	Depends on size of trailer (33-50)
Straight Truck	41'	8'6"	13' 6"	21-25
Straight Truck *(With annual wide load permit)**	41'	12'5"	13' 10"	21-25
Truck Tractor/ Semi-Trailer	53' Trailer	8'6"	13' 6"	Typically 36 bales to a load
Truck Tractor /Semi-Trailer *(With annual wide load permit)**	75' Trailer	12'5"	13' 10"	Maximum is approx. 81 bales (more than likely not allowable due to weight)
Implements of Husbandry	No Restriction	No Restrictions	13'10"	One Tractor may pull up to three trailers

Table 1: Vehicle Dimension Restrictions on Iowa Roadways with and without

Oversized Load Permitting (Iowa DOT)

Transportation of biomass must meet state regulations for vehicle weight as well. The restriction most commonly used is Gross Vehicle Weight (GVW), and primary highways have a gross vehicle weight limit of 80,000 lbs. A truck tractor or flatbed combination will weigh approximately 40,000 lbs. Based on an average bale's wet weight of 1300 lbs and a 53-ft trailer hauling 36 bales, corn-stover transportation equipment meets these state regulations for vehicle weight.

On flatbed trailers or trailers without sides it is a driver's obligation to properly secure cargo using tie-down or ratchet straps. There are two main restrictions to consider when transporting corn-stover bales. First, the combined strength of the all the straps must be equal to one and a half times the weight of the load. Second, when securing cargo, one strap per 10 feet of cargo length must be used (figure 2). A time-consuming aspect of hauling biomass bales is the time required to secure bales onto the trailer.

Figure 2. Traditional semi-truck hauling systems utilizing manual bale securement.

Alternative high-capacity trucking systems have recently become available to provide transformative solutions for biomass feedstock securement. Revolutionary automatic load securement systems have automated load securement through use of hydraulically-driven securement actuators. Such a system is engaged wirelessly from the semi-truck cab and provides unique safety benefits, since the truck driver is never required to exit the cab during either loading or unloading. This automated solution eliminates 25 minutes per load of securement and load preparation and results in significant savings to the biomass supply chain.

Figure 3: Advanced automatic load securement trailer with significantly improved securement times

Bale Handling Systems

As mentioned before, a first-generation 25-million gallon-per-year cellulosic ethanol biorefinery will require approximately 18,500 semi-truckloads of bales per year delivered into the plant gate. This equates to nearly 60 truckloads per day delivered to the biorefinery 6 days per week. This significant bale-handling logistical challenge requires that transportation and handling systems be optimized to eliminate system inefficiencies, and appropriate new technologies should be brought online to enhance the unit operations needed to load, offload, and transport biomass bales.

A variety of equipment exists currently to handle bales of biomass feedstock, and the capacity and commercial scale suitability of this equipment varies. Low-cost solutions for

handling large square bales with tractors are common for low-capacity operations, but do not meet the industrial-scale demands of a biorefinery (Figure 4).

Figure 4: Tractor mounted bale spear used to maneuver bales of corn stover at the edge of a field.

Moderate-capacity systems mounted on telehandlers provide quick and nimble bale maneuvering, but lack top-end capacity (Figure 5).

High capacity bale-squeeze systems enable the largest reduction in unit operations and also induce the least physical impact on the bales by eliminating spears used to secure the bales in tractor and telehandler-mounted solutions (Figure 6). Average bale-handling times vary based on the type of handling system used. Biorefinery feedstock-receiving stations will require multiple bale-handling systems to be simultaneously operational to keep up with the more than 60 trucks per day of incoming feedstock.

Figure 5: Telehandler mounted three bale spear

Figure 6: Industrial scale bale squeeze system

Data Acquisition Process

The data acquisition process was conducted in two stages:

1) Transportation-Parameter Data Collection

2) Handling-Parameter Data Collection

Data collection methods and activities are presented in the table below.

Method Utilized	Activity	Repetitions (Fall 2011)	Repetitions (Fall 2012)
Time Lapse Camera	Unloading, Unstrapping	17	45
GIS & GPS Data Acquisition	Speed, Distance, Delay	-	388
Mobile Camera	Loading, Load Securement	17	16

Table 2 Data Acquisition Summary

More details about data acquisition methods and results will be presented later in this chapter.

Transportation Parameter Data Collection

A dedicated data acquisition system was developed to collect transportation metrics related to vehicle operation, The system consisted of an embedded GPS data-logging device and telemetry-based data transfer equipment. More than ten trucks were instrumented with this setup, providing about 60 days of constant GPS tracking. Information transmitted from GPS units through an RS-232 serial interface was delivered to the CDMA wireless standalone modem and delivered to a data storage system located at an Iowa State University- Agricultural and Biosystems Engineering department location (Figure 7).
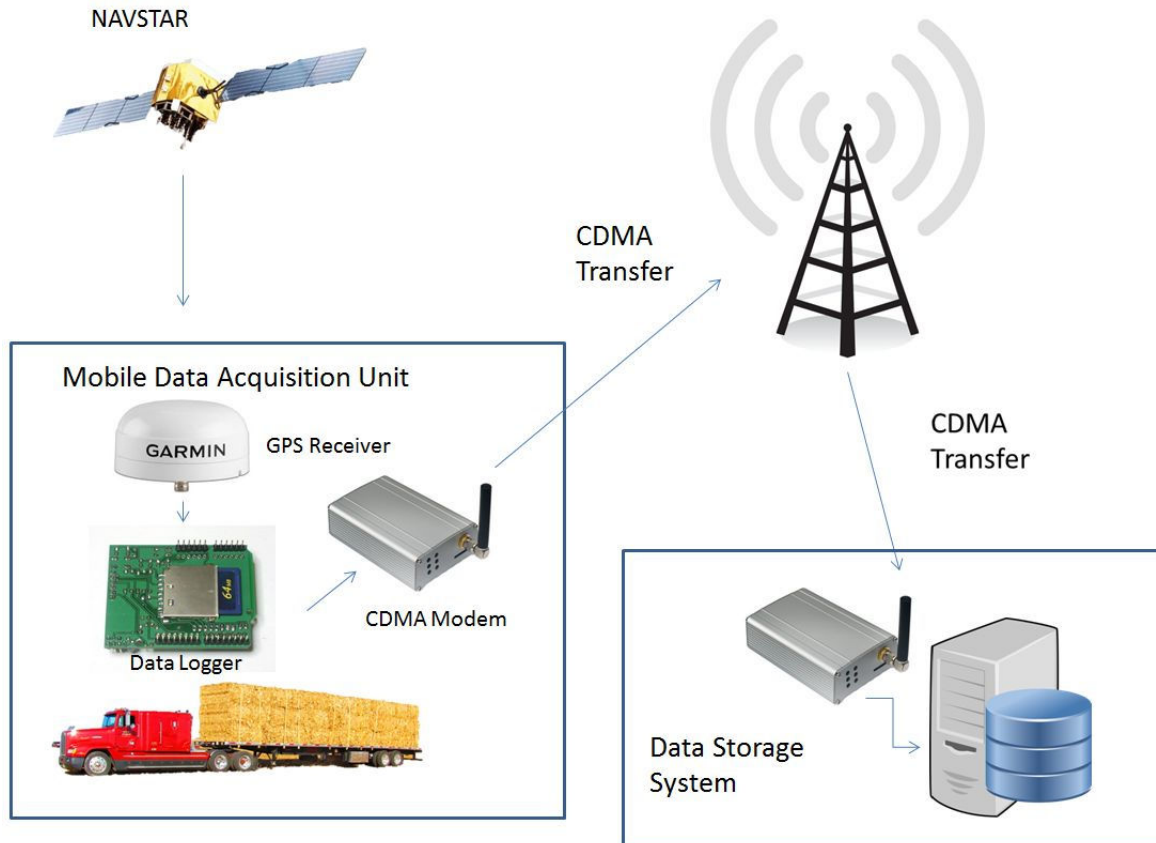
Figure 7. Dedicated transportation data acquisition system developed for the study

The server data was organized by date and vehicle number. This allowed adequate GIS map generation and analysis on daily basis. Collected parameters included:

1. Latitude

2. Longitude

3. GPS Speed

4. Engine Speed and Torque

ArcGIS and AgLeader SMS were utilized to conduct spatial analysis and data visualization. Once raw data from the data logger was loaded into the Ag Leader SMS 11.50 it was easy to create a spatial map comprised of several transportation cycles. Each transportation cycle was presented as a consecutive data point array (Figure 8.) in which each data point (GPS

position) contains attributes such as vehicle speed and UTC time-stamp with a one-second temporal resolution. The data set allowed reconstructing of vehicle activities during working hours and collecting Information described above. Through GIS data processing, several key performance indicators were obtained:

1. Transportation speed distribution

2. Biomass transportation distance distribution

3. Road winding factor

4. Time at the loading site (Total time at the field.)

5. Time at the unloading site (Total time at the storage site.)

6. Time on the road loaded.

7. Time on the road empty.

Figure 8. Ag Leader SMS 11.50 Spatial Map Detail

The winding factor is a coefficient used to estimate real travel distance using vector distance between two points on the road network. It is basically an overall road mileage between two locations divided by the vector distance between them. Using GIS data that included GPS tracking of semi-trucks during corn-stover transportation, the winding-factor distribution was obtained.

ArcGIS software allowed proper querying for locating specific activities on the field. Specifically, in cases where GPS speed indicated vehicle idling, it was easy to determine total time at the loading or unloading site. Movement direction (field to storage or storage to field) served as an indicator of empty or loaded vehicle status.

Handling Parameter Data Collection

The loading/unloading dataset was obtained using on-field video captures. A dedicated camera was positioned on the loading site of the supply chain. Similarly, unloading-site activities were fully covered with a time-lapse camera positioned on a 60-foot camera pole to obtain aerial views and adequately cover the whole manipulation area (Figure 9.)

After processing video captures in video-editing software it was easy to determine the following data types:

1) *Loading/ unloading time distribution*

To obtain relevant data with respect to the loading process from video captures, this operation was observed in cycles. Each cycle consisted of several operations such as: bale-pick up and lift, full loader travel, bale drop and empty loader travel. Time duration of the loader turnaround for each loading cycle was measured and documented. As mentioned earlier there were two types of loaders examined during data collection.

2) Securing the load- strapping time distribution

The strapping process typically starts after first bale is loaded. From that point the truck operator works on strapping until all bales are completely secured. In some cases strapping procedure duration can exceed loading procedure so the truck may be additionally delayed. The strapping procedure was observed along with the loading procedure and loading+strapping time was fully documented and presented in this study.   The same data types were obtained for the two different loading/unloading systems previously described in this article.

1)   Classic Strapping System

2)   Hydraulic ALSS (Automatic Loading Strapping System)

This allowed the two different load-securing systems to be compared in terms of time efficiency.

As described in the introduction of this article, a variety of equipment to handle bales currently exists. During the study, two types of loading system were examined:

1) A Telehandler-mounted three-bale spear, used to load 3 large square bales simultaneously

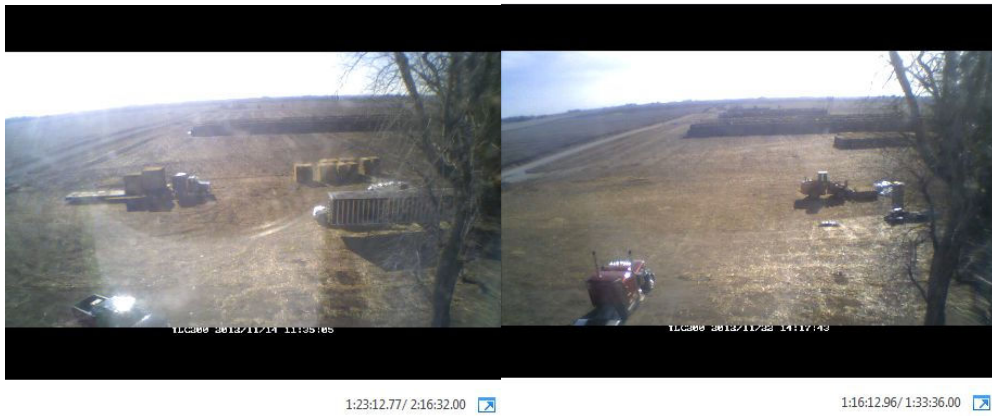2) An industrial-scale bale-squeeze system, used to load 6 large square bales simultaneously

Figure 9. Dedicated Time-Lapse Camera with 60 ft Camera Pole

The loading and unloading time distribution for large square bales represents one of the most important parameters for modeling, although previous studies have not provided this type of dataset. Without those two parameters it would be impossible to establish accurate representation of a truck-delay function, with a negative effect on overall supply-chain productivity assessment.

Results

Transportation Data Distribution

GIS queries were used to determine transportation distance and speed data. Data was obtained using 388 transportation cycles operating during harvest 2012. This dataset may represents a valuable resource for transportation-cycle modeling and assessment.

Transportation speed

As described earlier, this parameter was obtained from the GPS unit and delivered via a telemetry-based data transfer system. Each repetition provides the average speed of the truck in a single transportation cycle representing two principal categories:

1. Average Travel Speed Distribution for Empty Vehicle (Figure 11.)
2. Average Travel Speed Distribution for Full Vehicle (Figure 10.)

In both cases a normal data distribution is obvious. Variability among data results from different road surface types and traffic conditions. In some cases high travel speeds are the result of low traffic density and a high percentage of highway miles in travel distance.

These average and standard deviation values can be integrated into a model using a random-number generation function and multiple iterations. This approach would potentially allow examination of different transportation scenarios.
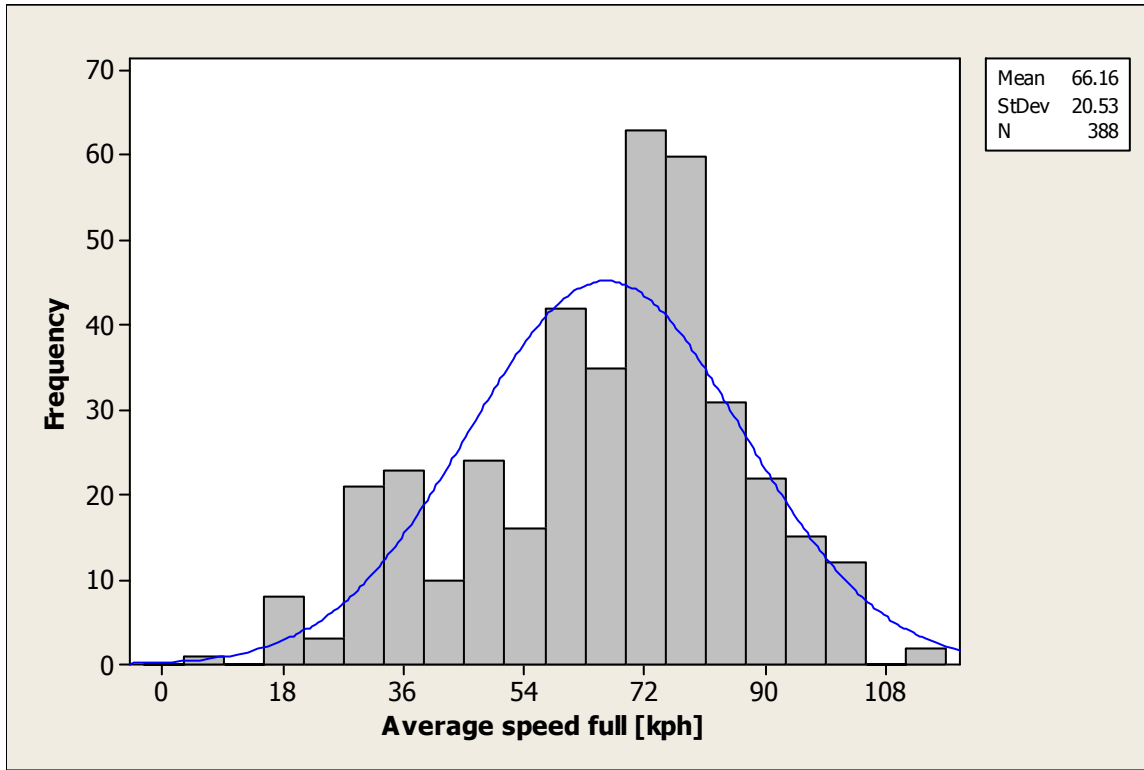
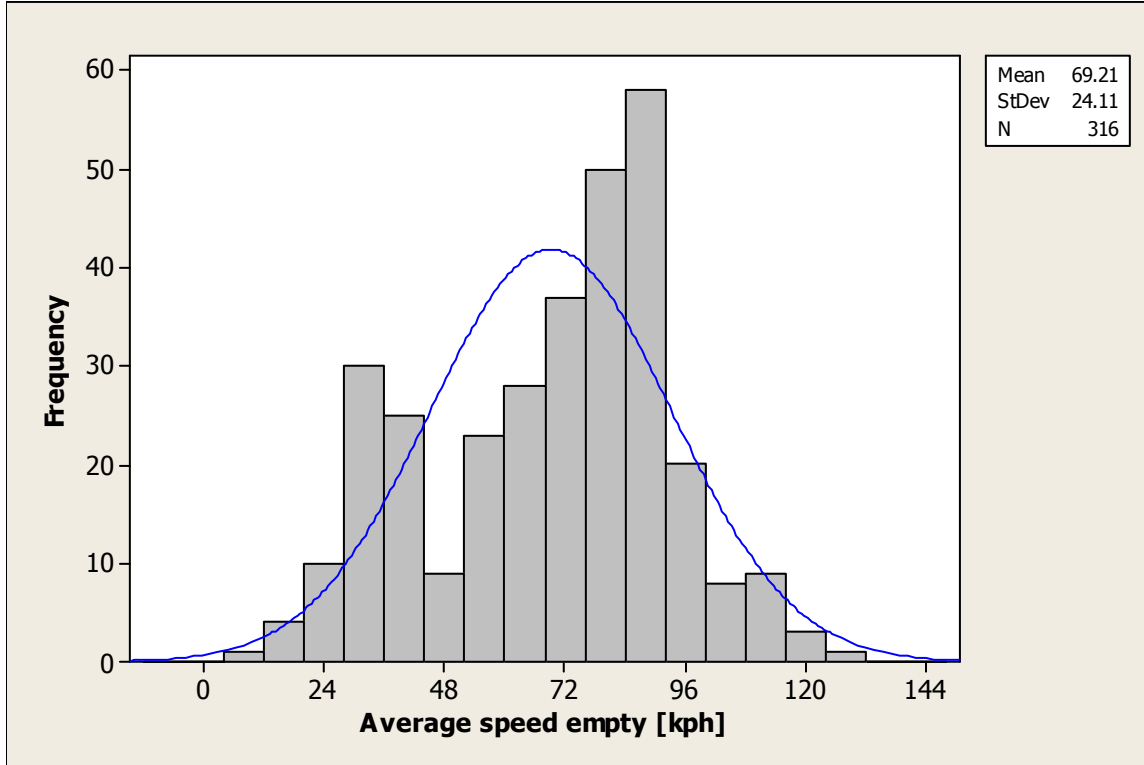**Figure 10 Average Travel Speed Distribution for Full Vehicle Movement**

Figure 11 Average Travel Speed Distribution for Empty Vehicle Movement

Average speed distribution for empty vehicle movement had a slightly higher mean and median value. Road conditions and number of miles on gravel and pavement were identical in almost all repetitions since those vehicles tend to use same route for both empty and full movement so these factors had no influence on difference between empty-vehicle movement speed and full-vehicle movement speed. Variability among data is similar for both cases and can be categorized as relatively low (Figure 12.) Extremely high differences between average speed for empty and full vehicle might occur only for those transportation cycles that included many stops and turns, since there is significant difference in acceleration rates for full and empty vehicles.

To make precise inferences regarding mean values for the average speed in full and empty vehicles an Analysis of Variance Test (ANOVA) was conducted (Table 3).
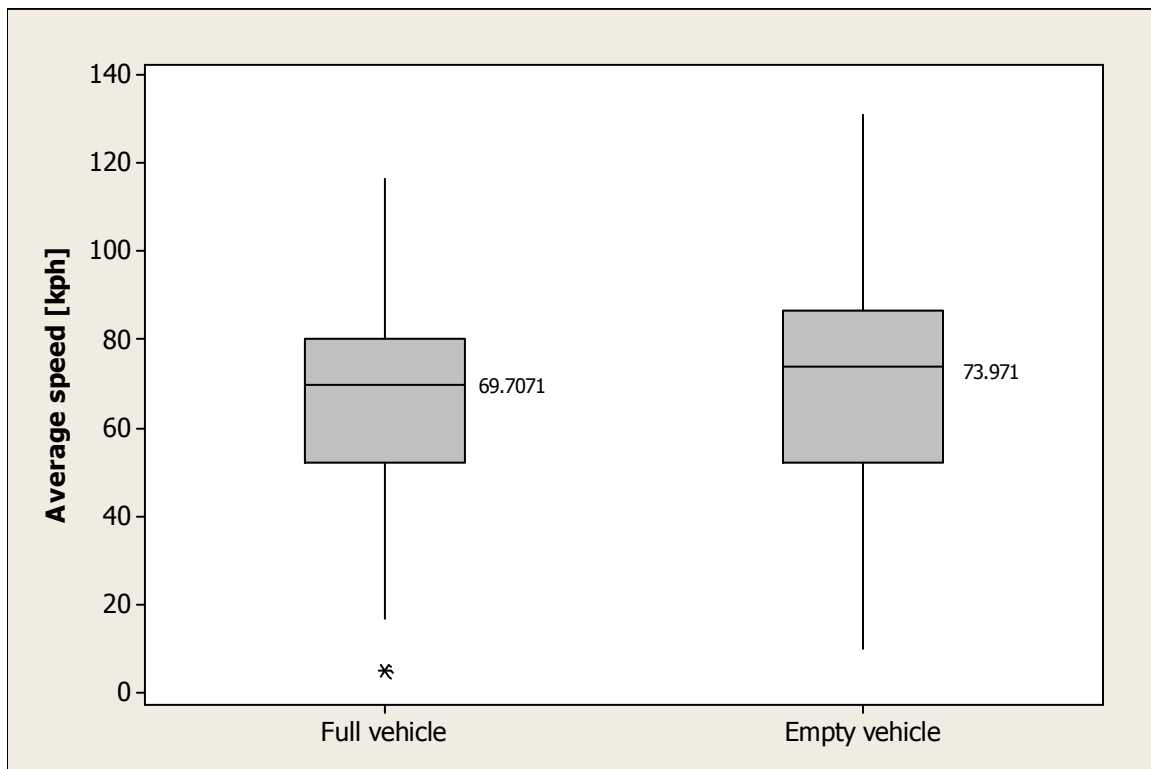
Figure 12. Boxplot of Average Travel Speed for Empty and Full Vehicle Status

Groups	Count	Sum	Average	Variance
Empty Vehicle Speed	388	25669.61	66.15878	421.3136
Full Vehicle Speed	316	21870.28	69.20974	581.4083

Source of Variation	SS	Df	MS	F	P-value	F crit
Between Groups	1621.133	1	1621.133	3.287295	0.070245	3.854739
Within Groups	346192	702	493.151			
Total	347813.1	703				

Table 3. Summary of Single Factor ANOVA Test with 95% Confidence Interval

By considering p-values from Table 3 it is reasonable to conclude that the difference between average speed for empty and full vehicles is not significant, based on a 95% confidence interval. The low-speed difference might be result of a small number of turns. This specific characteristic will be considered in more detail later in this chapter by introducing a road winding factor. Another factor that also might explain this insignificant difference is obviously low cargo weight. As outlined before, Gross Vehicle Weight (GVW) in corn-stover hauling will be approximately 30,000 lbs. The upper vehicle weight limit is 80,000 lbs for the truck tractor combination used, reflecting a significantly low utilization of truck-towing capacity.

Transportation Distance Distribution

As described in the methods section, distance assessment was conducted using GIS software and vehicle-tracking data for biomass transportation in 2012. Unlike the average transportation speed, transportation distance expressed a certain skewlevel (Figure 13). It is obvious that the highest number of occurrences occurred for distances of between 2 and 6 miles, and almost 45% of all transportation cycles fall into this range. The reason for this is a result of storage location strategy.
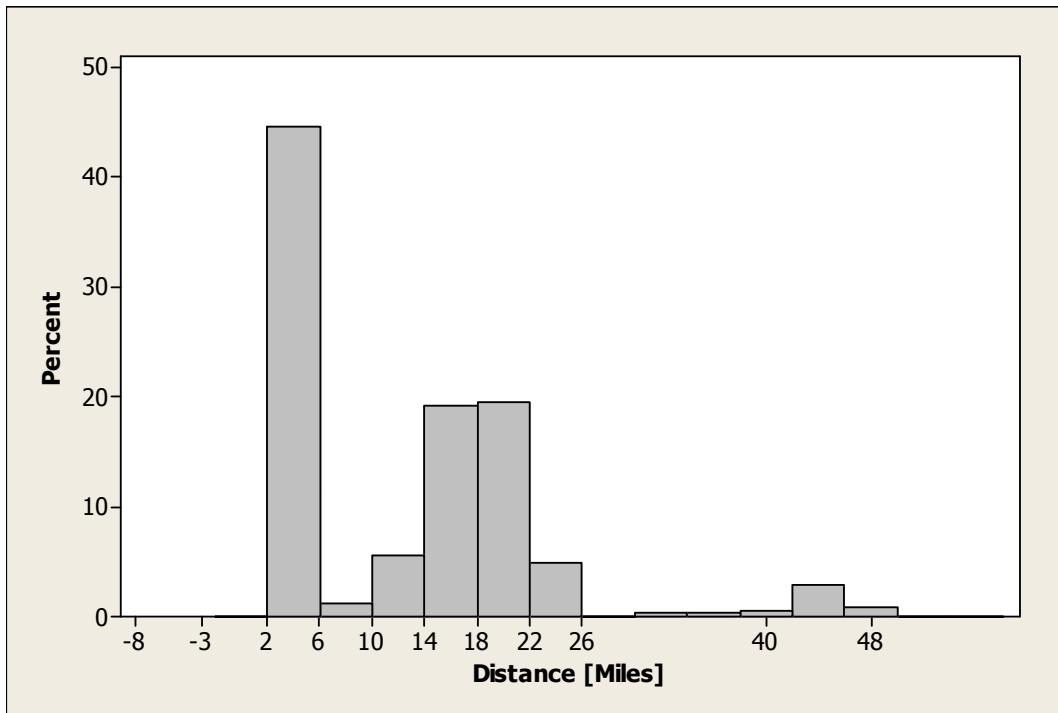
Figure 13. Travel Distance Distribution for the 2012 Biomass Collection Process

Biomass satellite storage units were usually located in locations chosen to minimize travel distance for all harvested fields. The second peak appears between 14 and 22 miles and frequency for this distance range is also significantly high.

Therefore, the distance distribution for the 2012 biomass collection can be described as bimodal. This conclusion was made using 343 repetitions.

Road winding factor

The winding factor is a coefficient used to estimate real travel distance using vector distance between two points on the road network. It is basically overall road mileage between two spots divided by vector distance between them. Basically, if a vehicle is driving on a straight road with no turns, the winding factor would be 1. In other words if we know the vector distance

between two locations and we want to know real distance in road miles, it would be necessary to multiply road winding factor by vector distance between those two locations.

Using GIS data that included GPS tracking of semi-trucks during corn-stover transportation, winding factor distribution was obtained (Figure 14.) Transportation took place on freeways and local roads in Story, Hamilton, Boone, and Marshall Counties. By using the winding factor we include more accurate values for travel distances for cases in which we measure the distance in vector format. This is usually useful in modeling and planning processes where we can obtain distance between two locations of interest without tedious measurement of road network segments in GIS. Earlier in this chapter it was observed that low differences between average speed for full and empty vehicle movement resulted from a low number of stops and left turns. This can be confirmed by the obviously low road-winding factor with mean value 1.485, indicating a low number of turns (Figure 14.)
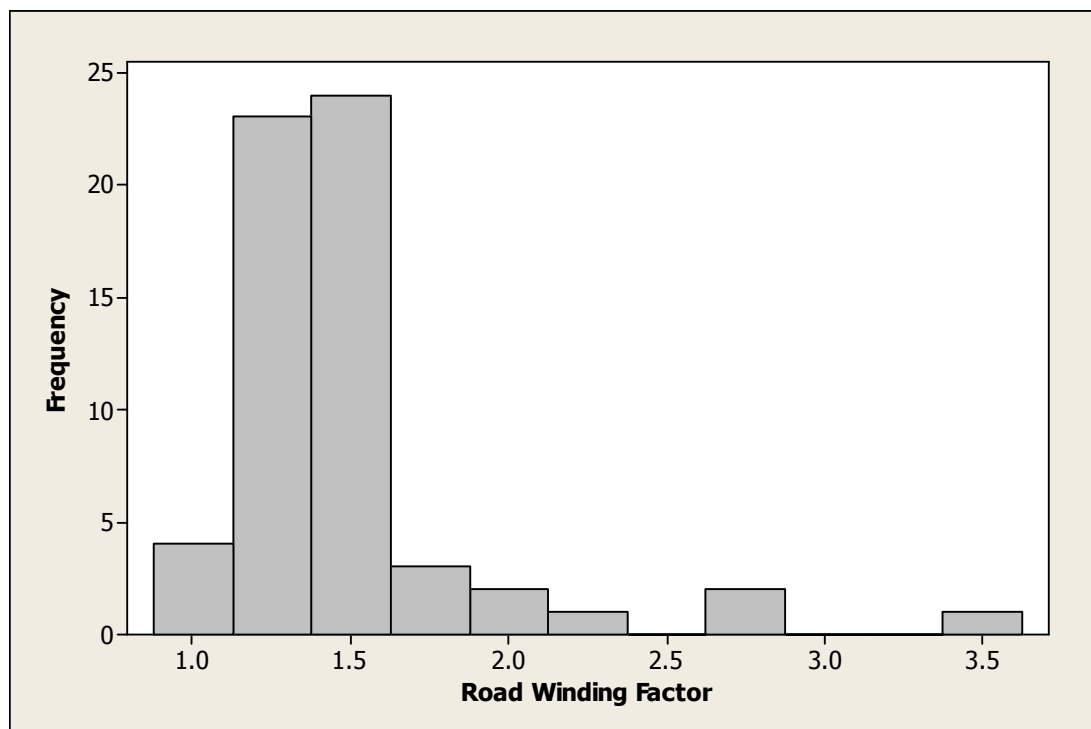

Figure 14. Road Winding Factor from 2012 Biomass Hauling Data

Time at the loading site (Total time at the field)

Intensive GPS tracking during Fall 2012 allowed complete analysis of vehicle movement. Vehicles hauling biomass bales typically spend significant amounts of time at the loading site for several reasons:

1) Vehicle queuing due to insufficient number of loaders

2) Load-securement procedure

3) Vehicle checkup or maintenance

To increase productivity and vehicle utilization it is essential to reduce total time at the loading site.

The first measured parameter was total time at the loading site. This parameter was captured using GPS data implemented into a GIS spatial map. It was easy to determine time spent at the loading location since the spatial map included a shape file of the field locations. Using this tool it was possible to capture the exact time when each truck arrived at the field and the exact time when it exited the loading site. Parameters were monitored during the whole period of biomass hauling for the Fall 2012 season.
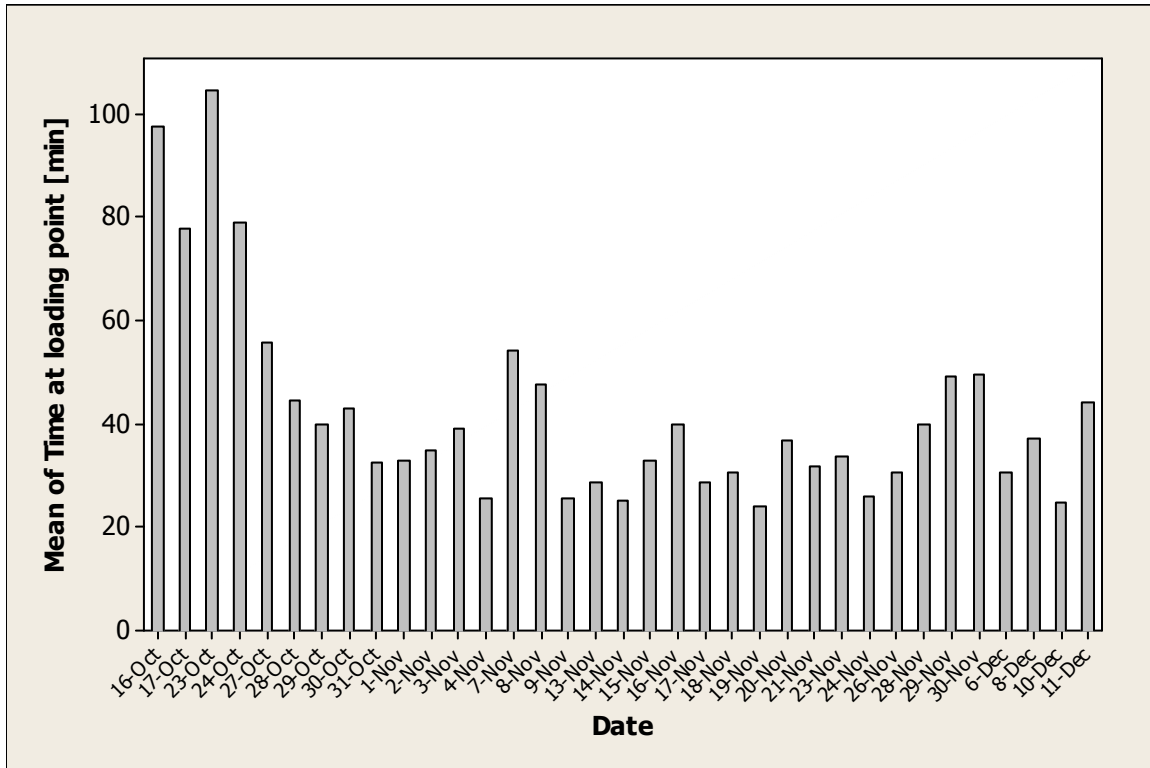
Figure 15. Chart of Mean Time at Loading Point

It is obvious from Figure 15 that mean time at the loading site exhibited highest values in the first week of the transportation season. This period is basically a preparation period that drivers, machinery operators, and other personnel need to adequately start the season. It includes various activities beside the actual transportation, including storage site preparation, personnel training, etc. Moreover, since this is a seasonal activity, drivers, operators, and other personnel require a certain time of adaptation. During this period vehicles exhibit greater delay than at later dates when the whole team has completely adapted to new activities that gradually have become an everyday routine. It is obvious from Figure 16 that the first week of the season is also characterized by low transportation frequency. Data points in this specific part of the scatterplot are sparsely distributed, unlike those for the period after October 26th where data points exhibit high density.
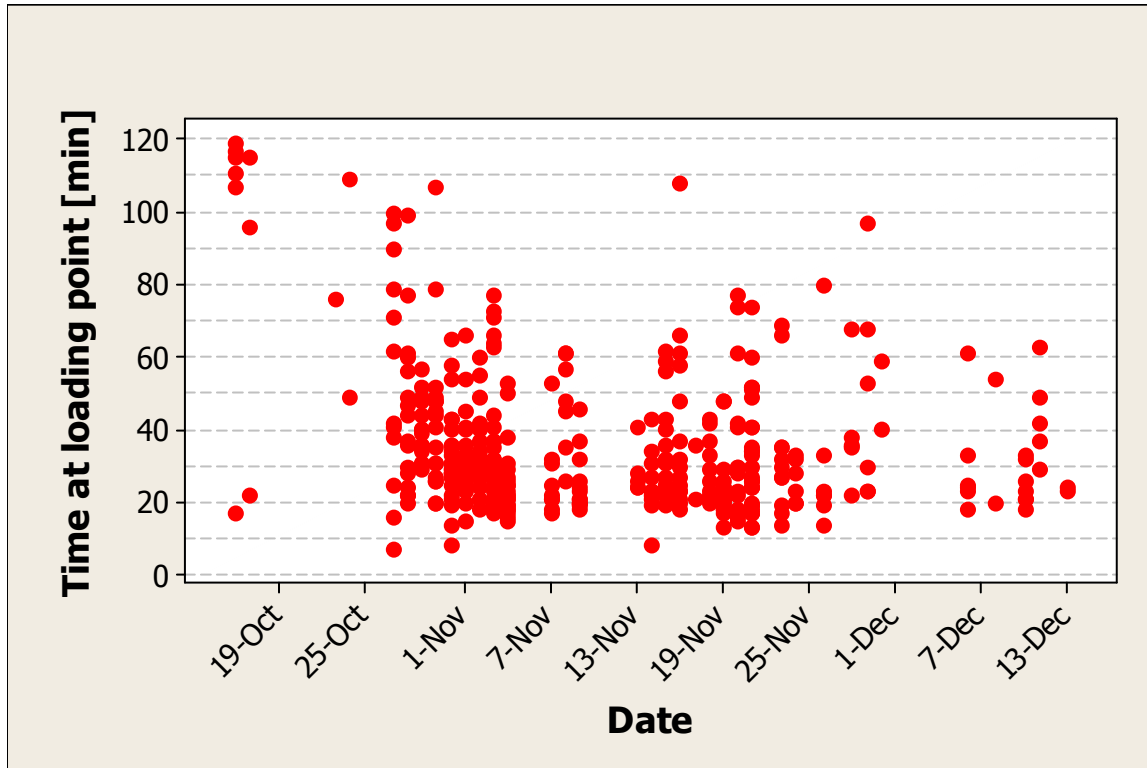
Figure 16 Scatterplot of time at loading point

However, this initial and less productive period must be included in all estimations and examinations since it is necessary in order to achieve higher productivity rates throughout the remainder of the season.

Time at the unloading site (Total time at the storage site.)

As expected, time at the unloading point had a similar scatterplot pattern (Figure 18) and the chart of mean time at the loading point is also similar (Figure 17). Basically all activities at the unloading site are nearly identical to the loading-site activities, accounting for the similarity. Unlike the shapes and pattern of the loading/unloading plots, the mean values are different. The

histogram of time at the loading site is consistent with normality of the data distribution and the

mean value is 37.19 minutes (Figure 19).
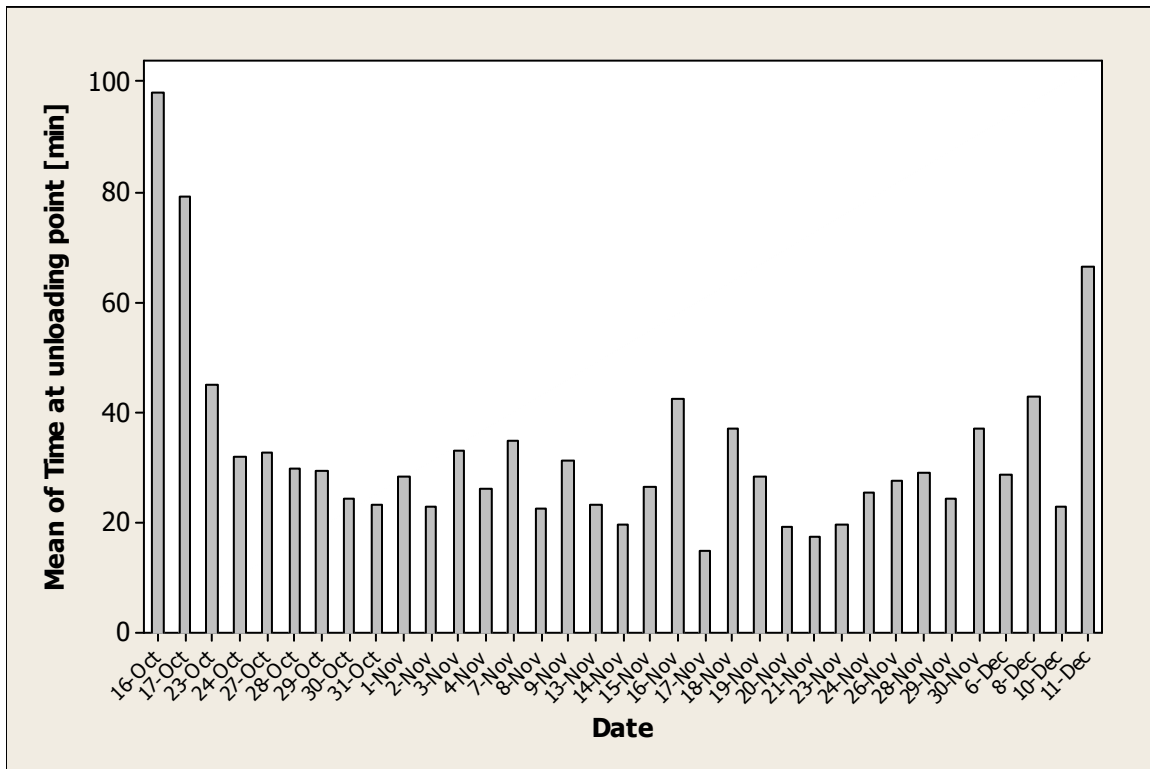
Figure 17. Chart of mean time at unloading point

The mean time at the unloading point was 29.10. This difference is to be expected since

the loading process usually takes longer than the unloading process. The loading procedure is

followed by load securement using ratchet tie-downs. This process is often tedious and time-

consuming, with additional excessive truck delays in some cases of low visibility or wind gust.

Those excessive delays may be recognized as outliers on Figures 16 and 18. During the whole

season only one telehandler was working at both the loading and the unloading site.
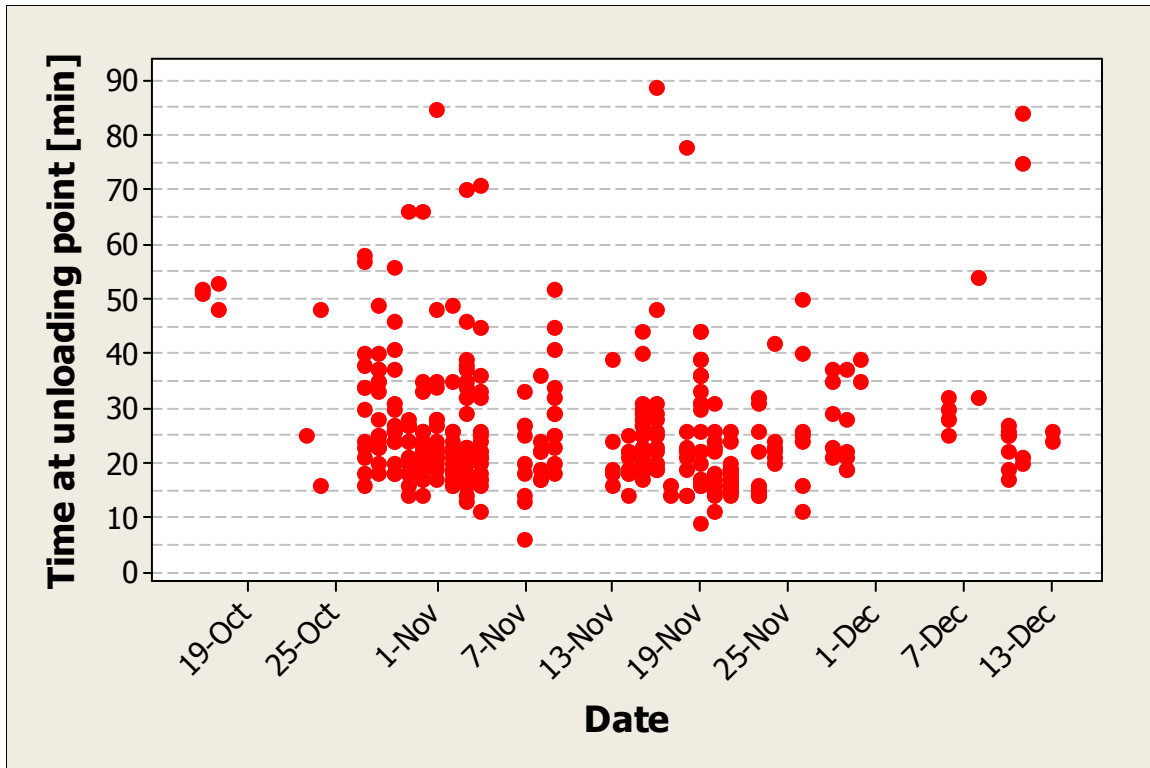
Figure 18. Scatterplot of time at unloading point

It is obvious that load securement was not the only factor producing truck delays. Vehicle queuing is also a very important factor that must be examined in more depth. A few more details about queuing effects will be explained later in this article. It is essential to understand that truck delay in most cases exceeded time needed to load and secure the truckload. Everything except actual loading and cargo movement must be categorized as unproductive time within a transportation cycle and must be reduced or completely eliminated from the system.

Figure 19. Histogram of time at loading point

Figure 20. Histogram of time at unloading point

Vehicle Loading and Unloading Time Distribution

During the study, two types of loading systems were examined:

1)   The Telehandler, a mounted three-bale spear, used to simultaneously load 3 large square

bales (Used during Harvest 2012)

2)   An industrial-scale bale-squeeze system, used to simultaneously load 6 large square bales
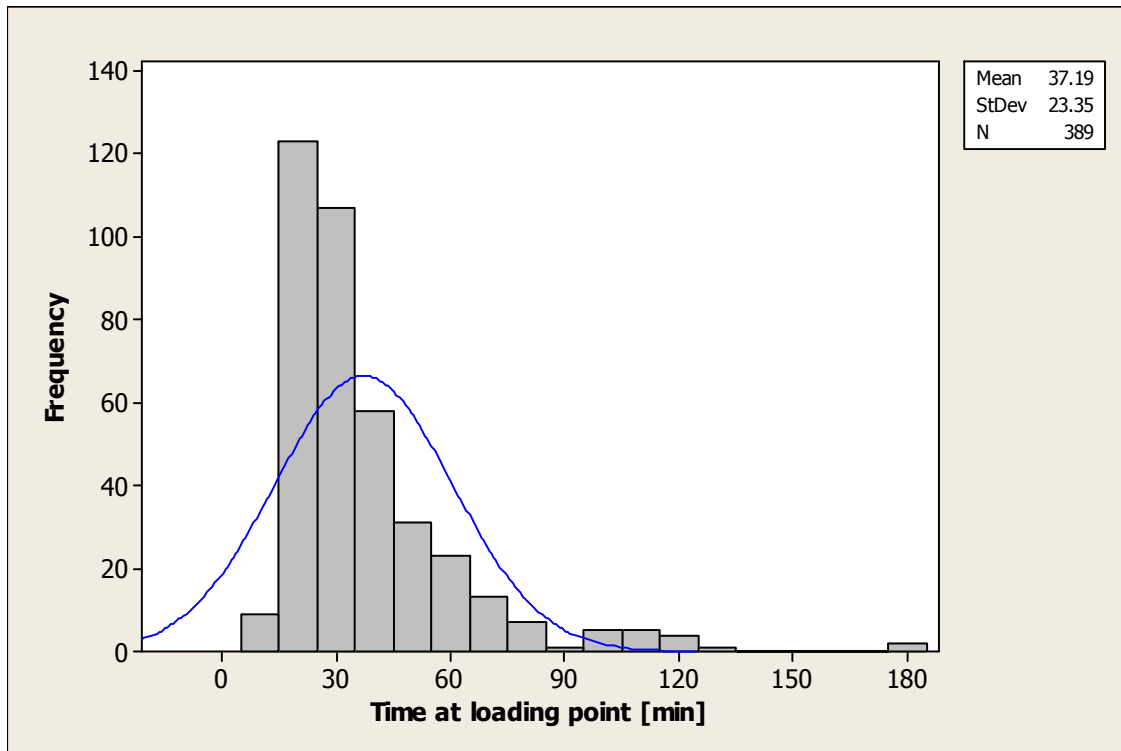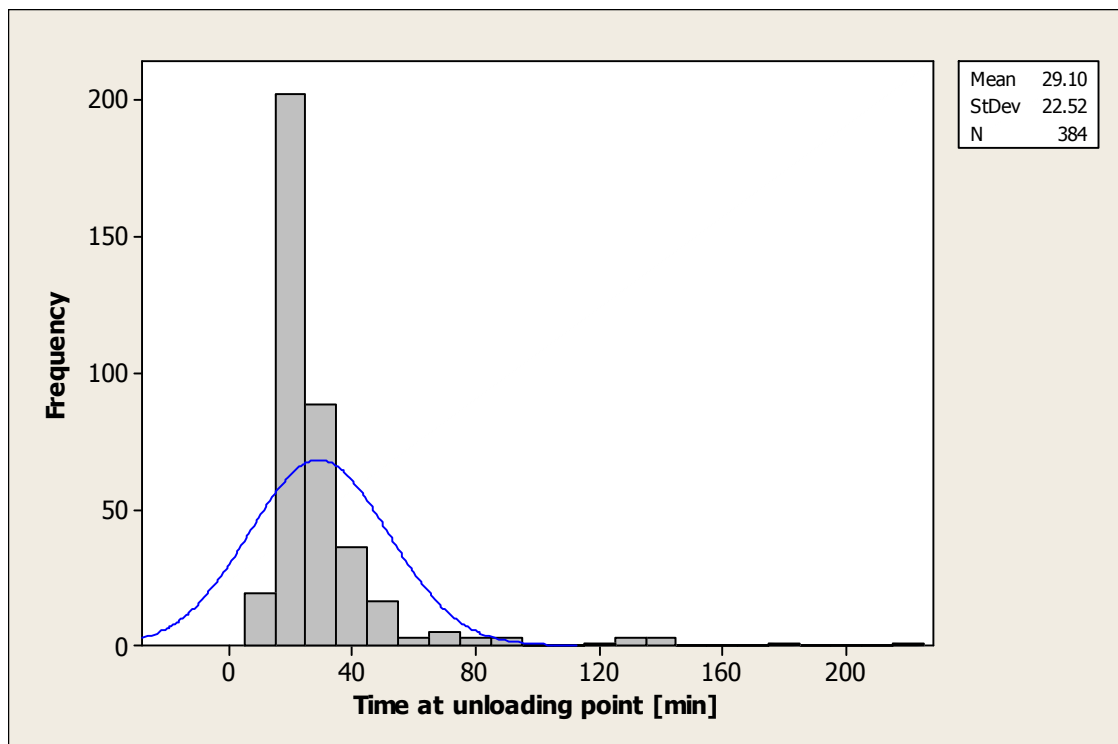
(Used during Harvest 2011)

As described in the methods section of this paper, a strapping process typically starts

after the first bale is loaded. From that point on the truck operator works on strapping until all

bales are completely secured. In some cases the strapping procedure duration can exceed that of

the loading procedure so the truck may be additionally delayed, as described earlier. The

strapping procedure was observed along with the loading procedure and was fully documented

and presented in this study.

	Average Loading Time	Average Strapping Time	Total Loading Delay
Telehandler	12.16	12.80	24.96
Standard Deviation	1.82	6.81	6.59
Squeeze Loader	13.91	11.2	18.48
Standard Deviation	6.82	1.57	6.39

Table 4 Summary of loading and strapping times

The loading-time distribution shown in Table 4 considered a classic strapping procedure

using ratchet tie-downs. Loading time without the strapping procedure is basically the time

needed for a loader to form a truckload. Any additional delay is caused by strapping. The mean

values from Table 4 show that the difference between those mean values is significant, so

eliminating the strapping procedure can decrease truck delays and increase truck productivity,

especially if we take into consideration that a 25 million gallons per year cellulosic ethanol

biorefinery will demand 18,500 loading procedures each year. Although an adequate load

securement procedure is mandatory for all trucks moving biomass on Iowa roads, there are technical solutions that can automatically secure the load without the manual strapping procedure. Such an automated load-securement system and its influence on overall truck delay will be described later in this study.

Average loading time using the squeeze loader was 13.91 minutes, but the whole loading process takes 18.48 minutes on average, so the difference between those two values can be defined as additional truck delay needed to complete the strapping procedure whose average value was 4.57 for the squeeze-loading system used during Harvest 2011. In the case of the telehandler, used during Harvest 2012, loading took 12.16 minutes while the whole loading process took 24.96 minutes on average, so the additional strapping delay in this case was 12.8. Although loading times had very close average values for both years, additional strapping delay was almost three times higher in 2012 than in 2011. The main factor contributing to this difference was due to a labor organizational strategy. During 2011 trucking teams had more trucks per loading site and queuing length was higher than in 2012, so truck operators sitting idle in the waiting line were instructed to help trucks in front of them finish strapping. During Harvest 2012 there was no such organizational pattern, resulting in a higher average value of truck delay due to strapping and securement.

With respect to unloading, there is no simultaneous unstrapping and bale unloading activity as in the case of loading and strapping. Typically, truck operators tend to remove ratchet tie-downs before unloading starts. The unloading process was also examined for two types of loading equipment, telehandlers and squeeze systems. It is important to note that those values can significantly depend on machine operator skill and experience. Typical unloading times are presented in Table 5.

	Average Unloading Time	Average Unstrapping Time	Total Unloading Delay
Telehandler	9.66	4.26	13.71
Standard Deviation	2.42	1.13	2.86
Squeeze Loader	11.01	3.49	13.86
Standard Deviation	1.57	1.37	1.97

Table 5 Summary of unloading and unstrapping times

Difference in Loading Performance

The two loading machinery methods expressed different mean values and variability characteristics (Figure 21).
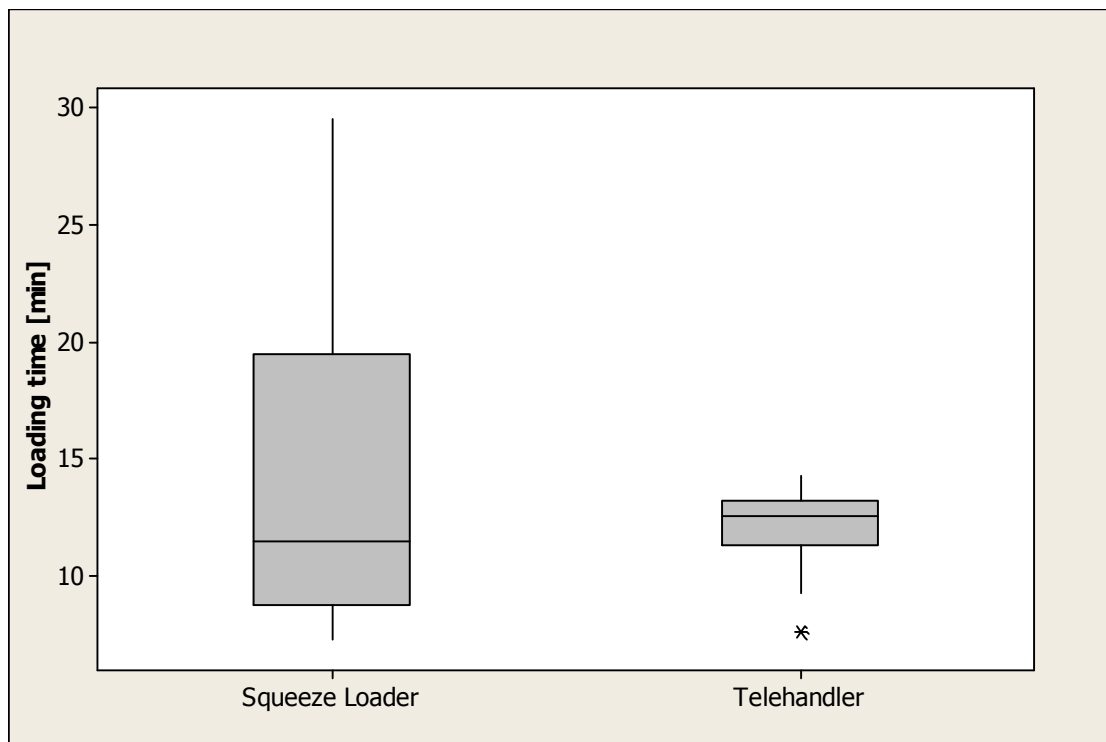

Figure 21 Boxplot of loading times for telehandler and squeeze loader

To provide appropriate conclusion regarding telehandler versus squeeze loader productivity an ANOVA test was conducted and presented below (Table 6).

ANOVA
SUMMARY

Groups	Count	Sum	Average	Variance
Telehandler	16	194.5	12.15625	3.297292
Squeeze	17	236.4	13.90588	46.51559

ANOVA

Source of Variation	SS	Df	MS	F	P-value	F crit
Between Groups	25.23182	1	25.23182	0.985483	0.328535	4.159615
Within Groups	793.7088	31	25.60351			
Total	818.9406	32				

Table 6. Single Factor ANOVA Test with 95% Confidence Interval for the loading machinery

By considering p-value from Table 6 it is reasonable to conclude that the difference

between average loading time for the two different loading methods is not significant, based on a

95% confidence interval.

Advanced Cargo Securement Solutions and Time Savings

The classic load-securing operation was typically comprised of the following activities:

1) Placing a strapping belt over the load

2) Attaching and preparing the belt for tensioning

3) Belt tensioning and checking

Using a traditional strapping and securement approach requires approximately 15 minutes

of time per truckload. An additional 5 minutes per truckload is required to unstrap the load at the

biorefinery. When scaled across the an entire biorefinery supply chain, nearly 8,000 hours of

time will be spent strapping and unstrapping feedstock load to supply a single 25 million-gallon-

per-year facility.

The ALSS is an automatic system with hydraulic belt tensioning elements that eliminates classic strapping activates (belt placement, attachment, and manual tensioning). Since overall loading time is comprised of loading and strapping this time is typically longer than strapping by itself. The main reason for this is strapping latency that occurs because strapping usually starts after the first bale is placed on the trailer, which can take several minutes.

Overall loading time for both classic and ALSS systems were measured using video surveillance. A boxplot of loading and strapping times for both systems are presented in Figure 22. In addition to time savings, using the ALSS can also improve overall safety. When using a classic strapping system, truck operators spend a significant amount of time on the road exposed to possible car accident arising from presence of bypassing vehicles. In addition to reduced traffic risk, ALSS can reduce liability from employee injury and lower insurance costs due to lower employee risk. A simple benefit-cost analysis can be employed to provide more detailed information about advantages of the ALSS. Such an analysis should include all relevant costs and potential incomes (Sinha and Labi 2007) and for this specific investment should take into account injury and fatal accident possibility rates, costs per single fatal or injury accident, and ALSS equipment cost.
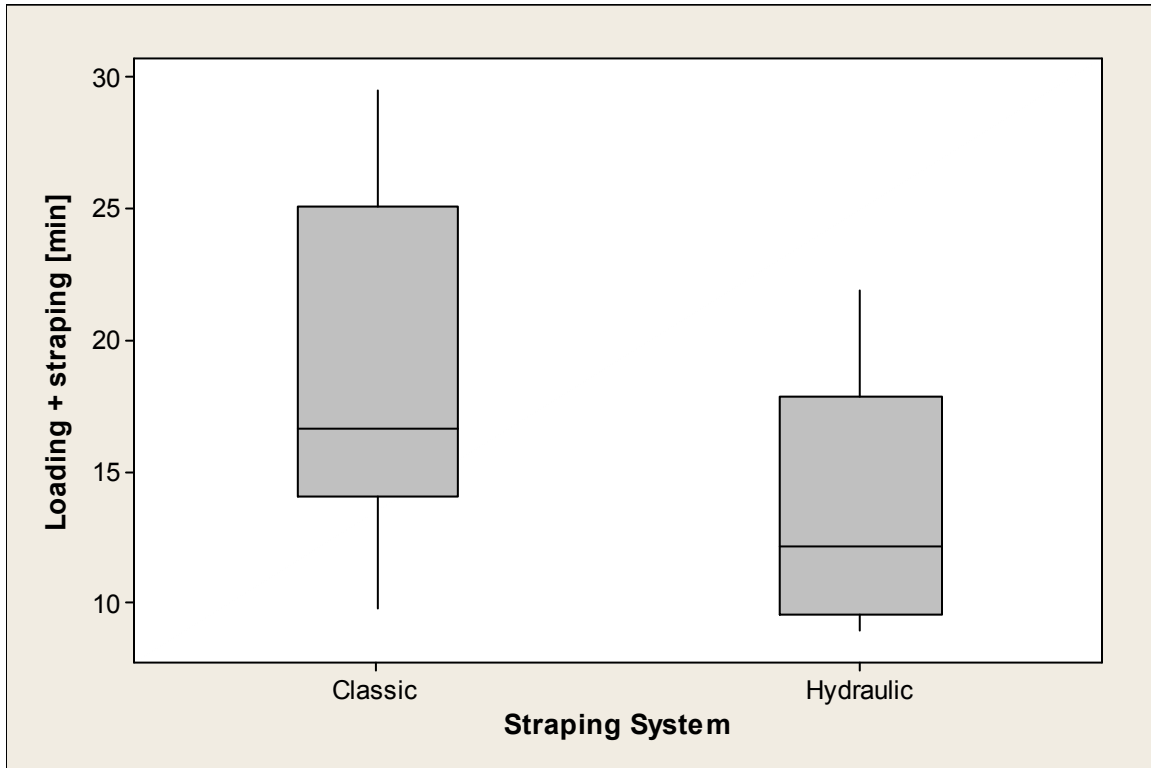
Figure 22 Advantages of the Automatic Load Securement System

Since the two different strapping systems expressed different mean values and variability

characteristics it was reasonable to utilize a single factor ANOVA test to make appropriate

conclusion regarding mean value difference.

Anova: Single
Factor

SUMMARY

Groups	Count	Sum	Average	Variance
Classic Strapping	10	198	19.8	37.32889
ALSS	7	91	13	19.29

ANOVA

Source of Variation	SS	Df	MS	F	P-value	F crit
Between Groups	190.4	1	190.4	6.322781	0.023813	4.543077
Within Groups	451.7	15	30.11333			
Total	642.1	16				

Table 7. Single Factor ANOVA Test with 95% Confidence Interval for the different strapping systems.

By observing p-value from the test (table 7) it was reasonable to conclude that ALSS achieved lower loading and load securement delays.

Truck Queuing Effect

Full-system optimization, with no additional truck delays except those caused by loading, unloading, and load securement activities, is hard to achieve in reality. It would mean that, once a truck arrives at a loading or unloading site, those activities start immediately. This is extremely rare in reality and quite often trucks must spend a certain time in a waiting line before a loader or unloader finishes the current task. Truck queuing time directly depends on the number of trucks in the waiting line and sometimes can cause significant truck delays that can be categorized as negative events. It is important to understand that it is not possible to completely eliminate truck queuing from the system, but it should be possible to minimize this negative effect. A fully-synchronized transportation cycle simply means that a truck always arrives at a moment when the loader is ready to start the loading task. To achieve this it is important to determine the number of loaders, unloaders, and trucks in such fashion that truck arrival frequency is synchronized with loading and unloading delay. This calculation takes into account time spent on the road, a function of a travel distance, so it is easy to synchronize truck arrivals with loading and uloading intervals for a single field-storage route. Unfortunately, industrial-scale supply chains can consist of several hundred fields, and each trucking team may change several fields in a single shift. What is optimal for one field-storage route is not necessarily optimal for another, so optimization is more about minimizing rather than completely eliminating truck queuing.

If we know average loading time, strapping time, and overall time at the field it is easy to derive average queuing time that at a loading site can be defined as:

Average Queuing Time = Average Time at Field – Average Loading & Strapping Time

Accordingly average queuing at the unloading site will be:

Average Queuing Time = Average Time at Unloading Site – Average Loading & Strapping

Time

This average time can be measured using video-surveillance equipment. In this study average values of previously-measured parameters were used to derive these values sufficiently accurately for problem illustration. Using the data set collected during the 2012 season, average queuing times were calculated and are presented in Figure 23.
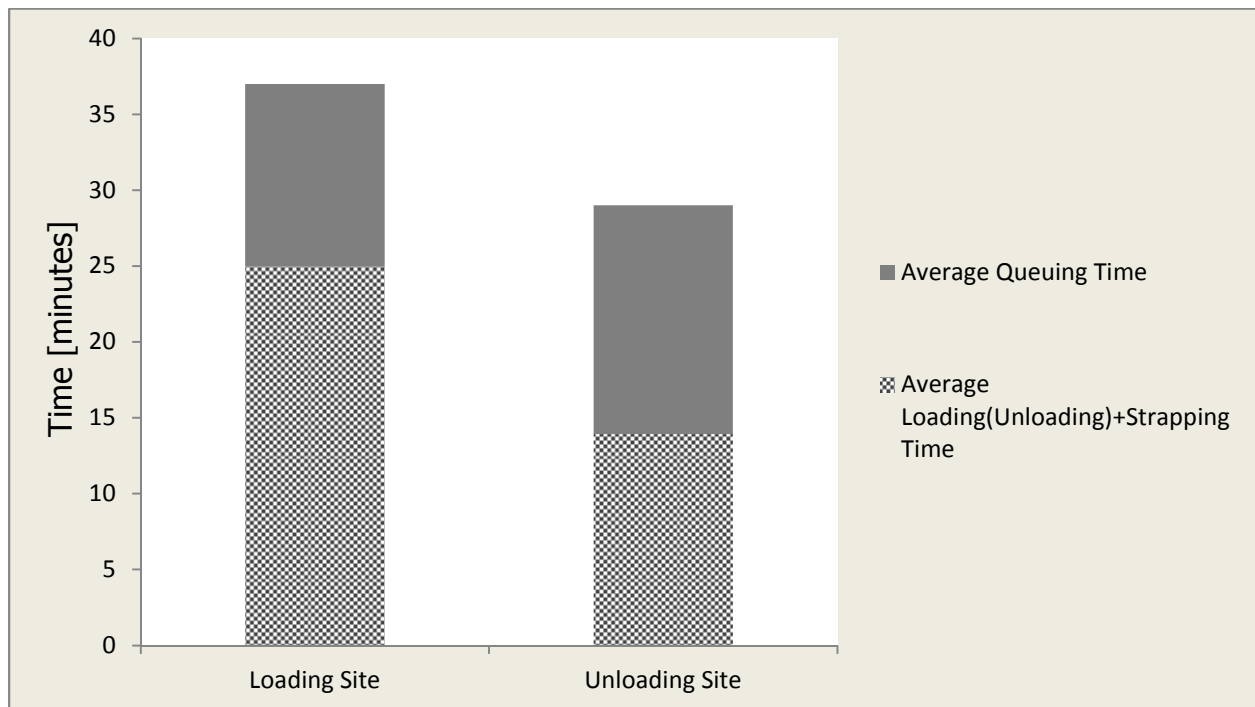
Figure 23 Impact of queuing time on overall truck delay at loading (unloading) site

It can be inferred from Figure 23 that queuing time has a large impact on overall truck delay. More than half the time spent at the unloading site can be attributed to queuing time or random delays caused by technical issues. By achieving synchronization and using a proper number of road vehicles and loaders, this unproductive time can be significantly reduced. To

determine those relevant factors it is necessary to conduct system modeling and to examine the influence of various factors on the overall supply-chain productivity and utilization.

Conclusion

To obtain the necessary conditions for supply chain optimization and modeling it is essential to provide reliable and accurate model inputs. Since those inputs are basically values for the model variables, the output accuracy will depend on them.

It is not possible to develop a proper decision-making process without a high-repetition data set. To obtain such a reliable data set for the corn-stover supply chain, advanced timing and tracking equipment can be utilized. The use of a Global Positioning System and a Geographical Information System can be essential in the data collection process. Data can be stored at remote locations using a telemetry system for data transfer. GIS software can perform queries and extract data so that relevant parameters such as vehicle speed, travel distance, and time at the loading or unloading site can be properly determined. Data distribution of such parameters leads to better understanding of current system performance.

Video surveillance was used for loading, unloading, and load-securement time measurement. Using GIS software it is possible to measure time at loading or unloading sites but it is not possible to determine specific activities conducted during that time. In order to measure exact times of vehicle loading, unloading, and cargo strapping, video surveillance was utilized. This data helped in determining unproductive time at loading and unloading sites caused by vehicle queuing.

Higher transportation productivity rates can be achieved by decreasing vehicle delays. Overall loading time can be significantly reduced using advanced systems such as an Automatic

Load Securement System (ALSS) that, by elimination of strapping procedures, not only improves transportation productivity but also decreases injury risk and driver fatigue.

REFERENCES

Appelbaum, E. and J. Berechman (1991). "Demand conditions, regulation, and the measurement of productivity." Journal of Econometrics **47**(2–3): 379-400.

CMSA-Huntsville (2013). Freight Transportation Modeling, UA Hutsville. **2013**.

Darr, M. J. and A. Shah (2012). "Biomass storage: an update on industrial solutions for baled biomass feedstocks." Biofuels **3**(3): 321-332.

EISA. "Energy Indepedence and Security Act of 2007-110th Congress" United States Senate, 4 January 2007

Kenedy, M. (2002). "The GlobalPositioning System and GIS." (CRC Press): 345.

Peyton, K. J. (2012). "Geographic Information System Tools for the Analysis of Commercial Level Multi-Pass Corn Stover Harvesting Systems." Thesis- Iowa State University.

Sinha, K. C. and S. Labi (2007). "Transportation Decision Making." (john Wiley & Sons Inc.).

Sokhansanj, S., et al. (2006). "Development and implementation of integrated biomass supply analysis and logistics model (IBSAL)." <u>Biomass and Bioenergy</u> **30**(10): 838-847.

CHAPTER 4. CORN-STOVER SUPPLY-CHAIN OPTIMIZATION AND MODELING

Abstract

Transportation logistics are an important factor in the improvement of bio-ethanol production efficiency. Large industrial-scale bio-ethanol production facilities must include well-organized and accurate delivery system. A single 25 million gallon-per-year cellulosic ethanol biorefinery will require 18,500 semi loads of bales to be delivered to the plant. The main two points of a corn stover delivery system are a loading point (corn field) and an unloading point (storage facility). All activities lying between these two points are interconnected and collectively they form the biomass supply chain. The goal of supply-chain optimization is to minimize the total cost of these activities (transportation cost per unit, inventory cost per unit, etc.) while satisfying the supply demands of a biorefinery. This study will report on a recent analysis using discrete modeling as its main methodology. Specific results presented include metrics for measuring supply chain efficiency, current capability of biomass supply chains, and sensitivity analysis of improvements with respect to future supply chains. The outcomes of this work will help in forming more efficient biofuel production processes and improve the biofuel life-cycle as well.

Introduction

Recent trends in renewable fuel production have revealed a completely new technology for cellulosic ethanol production. This technology uses corn stover as a main feedstock and has great potential for decreasing usage of fossil fuels. Because of its positive influence on the environment, the economy, and society in general, production of bioenergy is a main focus of many researchers in United States (United States Department of Energy, 2006). Many authors such as (Lau and Dale 2009) have described the potential for improving bio-ethanol production by reducing the costs of raw materials, equipment, and processing water. This recent progress in the field of bio-ethanol production is contributing to efforts to meet production requirements proposed by The Energy Independence and Security Act of 2007. This legislation states requirements for cellulosic ethanol increase in fuel production through year 2022 and specifically requires production volume to reach 16 billion gallons by 2022 (EISA 2007).

To improve production economics it is essential to develop an efficient and accurate feedstock-supply system, and transportation logistics is one factor that can contribute to successful and efficient recovery of energy from biomass (Searcy, Flynn et al. 2007). A modern scientific approach allows utilization of computer science in the field of modeling and simulation. This kind of analysis typically involves a large number of variables affecting overall system productivity and efficiency. These variables can take on different values and quite often they will have a stochastic nature. Simulation might be an adequate method for effectively dealing with such variables and their impact on overall supply-chain productivity (Lee, Cho et al. 2002). These authors also expressed the view that simulation is an effective tool for handling dynamically-changing variables and that it can be used for general optimization of the entire supply chain through finding local optimum values.

Similarly, Ingallis (1998) outlined the view that simulation is an excellent tool for evaluating the effectiveness of certain research scenarios. Using this approach a researcher may initially develop particular rules for modeling and, in subsequent analysis, system performance can be examined with respect to modification of these rules. This is a crucial part of supply-chain optimization since it allows consideration of various potential delivery scenarios. Each scenario may include different configurations of a number of specific elements. For example, it is possible to consider the full factorial number of supply chain elements, and to take into account every possible combination of these elements during each possible iteration.

Many authors, like Arns, Fischer et al. (2002), support a model-based analysis of supply chains. The approach in most cases includes estimating performance measures and resource utilization. In particular, it is possible to conduct complete and accurate optimization by simultaneously achieving maximal vehicle utilization and sufficient system productivity. However, maximizing utilization and productivity can demand certain trade-off strategies. For example, if we use an insufficient number of vehicles in the supply chain, productivity can be below the desired level even if these vehicles are maximally utilized. We can overcome this deficiency by simply increasing the number of vehicles within a system, but in that case their utilization might decline because of an insufficient number of loading channels at the transportation source. Similar conflicts can be observed from the aspect of loading equipment usage. If we have more loading channels than needed, most likely some of them will be poorly utilized. However, having more than enough loading channels will have a positive influence on transportation productivity, since it will eliminate truck queuing at the loading site. Therefore, the main optimization goal should be to achieve a condition that will satisfy both aspects (equipment utilization and equipment productivity). Moreover, when it comes to supply chain

performance assessment, some authors strongly recommended utilization of two or more performance measures. Beamon (1999) stated that supply-chain performance assessment with only a single performance measure is generally inadequate since it is not inclusive and basically ignores interactions among important supply-chain elements.

Supply Chain Modeling and Performance Assessment

Proper optimization must take into account many system-setup scenarios before making a final decision. Dukulis, Birzietis et al. (2008) used *AnyLogic* and *ExtendSim* software for biofuel supply-chain modeling and simulation. In their study they recommended a process for system improvement comprised of the following steps: *State the Problem, Investigate Alternatives, Model the System, Integrate, Launch the System, Assess Performance, and Re-evaluate.*

Similarly, when considering corn-stover supply-chain modeling it is necessary to take into account several unique properties of such a system to develop a system-improvement methodology. This methodology should include many scenarios including all possible combinations of system variables likely to occur in reality. The methodology developed for this paper is presented on Figure 24. The steps shown in this diagram will be discussed in more detail in the following sections.
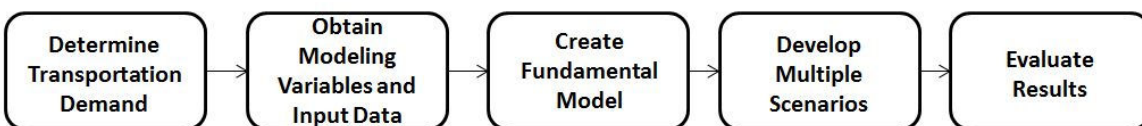

Figure 24 Supply Chain Performance Assessment Methodology

Transportation Demand

Transportation demand for cellulosic ethanol production depends directly on facility size. In particular, a single 25 million-gallon-per-year cellulosic ethanol biorefinery will require 18,500 semi loads of corn stover bales (Darr and Shah 2012). Such a volume will require corn stover from several hundred cornfields. This represents a huge potential for system optimization, since every improvement in a truck's transportation cycle will be multiplied by 18,500 during the season. Seasonal transportation demand can be presented on a daily basis if we take into account the seasonal biomass collection-time window. This window will strongly depend on seasonal weather conditions, and it typically ranges from mid-October to mid-December.

Transportation Origin and Destination

As described earlier, a transportation cycle typically starts at a corn field where biomass bales are loaded onto semi-trailers and transported to one of several industrial-scale biomass-storage locations that might include one of two different types of cellulosic biomass stacks:

1.) *Field-Edge Stack-* Short-term, temporary storage where all the bales from a particular corn field are grouped together to provide more efficient loading process. Biomass hauling typically starts at such a location.

2.) *Industrial-Scale Stack-* Long-term storage that constitutes the origin for the biomass-hauling process. This type of stack may exist in one of several forms, including open storage, tarped storage, permanent-structure storage, and anaerobic storage.

Development of Fundamental Corn-Stover Supply-Chain Model

The basic supply chain model must include all time-consuming activities that can affect overall transportation productivity. In particular, the corn-stover supply chain may consist of several hundred transportation cycles that follow almost identical patterns. All transportation cycles typically start at the corn field where biomass bales are loaded using a tractor-mounted bale spear, a telehandler-mounted bale spear, or a bale-squeeze system. After the vehicle is loaded, road movement using gravel or pavement road network will take place. At the destination, offloading is performed using the same equipment used for loading. These activities are presented in chronological order in Figure 25 and all will occur in any field-storage combination but with variations in travel distance and average speed for different fields.
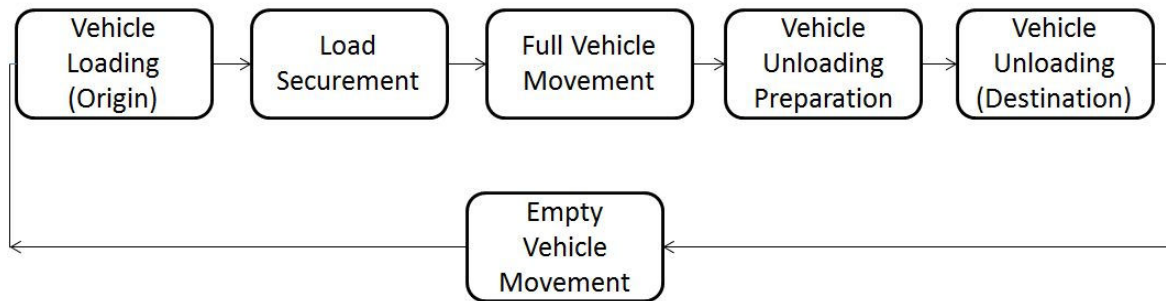

Figure 25 Corn-Stover Transportation Activities (Single Transportation Cycle)

To properly represent the activities in Figure 25 the modeling tool must be able to provide the several functions shown in Figure 26. It is important to emphasize that this modeling approach is based on transportation time as its main focus and, if all functions of Figure 26 are properly adjusted, the final model output will be delivery time duration for a single truckload.
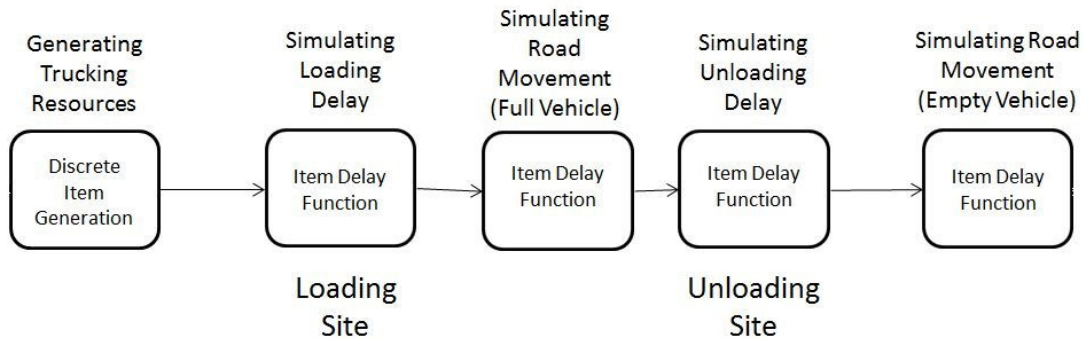
Figure 26 Discrete Model- Basic Functions for the Corn Stover Supply Chain

As mentioned before, all activities are expressed in time units meaning that some of them can be derived from other variables, e.g., time spent on the road can be derived from the travel distance and travel speed, etc. The described modeling approach will produce representation of only a single transportation route. In reality the corn-stover supply chain is composed of several hundred transportation routes corresponding to the several hundred fields included in the system. To examine different transportation routes using this model, the software should be able to provide multiple scenarios by altering one or more variables, and different scenarios will yield different model responses and thereby allow sensitivity assessment.

Research Objective

In this paper, we introduce relationships between transportation-team optimization, trucking productivity, bale-handling equipment efficiency, and transportation-time window. One of the most important parameters is the optimal number of road vehicles and loading/unloading machines, and biomass bales are treated as basic transportation units. Relationships between relevant factors will be examined using ExtendSim modeling software with a multiple-scenario

approach. Relationships and recommendations produced by this work can be used to determine optimal transportation equipment setups for satisfying overall transportation demand and transportation time window.

Methods and Materials

As was emphasized earlier, the goal of this paper is to more descriptively present key factors affecting transportation efficiency and cycle time optimization. Accordingly, transportation-system optimization should determine the optimal number of loading/unloading units and road vehicles. By successfully adjusting these two capacities, idle time in terms of either transportation vehicles or loading/unloading machines can be decreased to a reasonable level. A transportation team can be defined as number of semi-trailers and loaders/unloaders that operate within a certain radius so cycle-time optimization can be achieved by considering requirements mentioned above.

ExtendSim software was used to satisfy modeling requirements and provide appropriate representation of functions and activities presented in Figures 25 and 26. To be more precise, ExtendSim's discrete-modeling capabilities satisfied almost all modeling needs and provided convenient visual representation of all activities in the corn-stover supply chain. In particular, items such as loading and unloading delay or vehicle travel time were represented as process components (Figure 36). All activities were characterized with specific data distributions determined from field measurements and vehicle-tracking systems. The scenario manager tool allowed full-factorial assessment considering system variables to be either factors or responses. For example, this allowed quantification of the influence of loading time on supply-chain

productivity in bales per hour or the influence of number of vehicles, loaders, and distances on overall transportation productivity.

ExtendSim Modeling Software Features and Functions

As explained earlier, proper assessment of supply-chain system performance was established using ExtendSim 8 Modeling Software. Such discrete modeling is based on fundamental operational research methods that are an essential part of the modeling software. For example, the influence of the number of loaders on overall transportation productivity is a typical optimization problem in which the main goal is to select the number of servers at each station to achieve desirable results for the system.

The supply-chain model developed for this research is a representation of a realistic cycle of biomass transportation between single corn fields and biomass storage locations (Figure 27) . The transportation cycle model consisted of several components that simulate actual activities during transportation (Figure 27). By modeling realistic transportation cycle activities it is possible to estimate the impact of key factors (number of trucks, number of loaders, gravel and paved road segment length etc.) on overall performance of the system. Model inputs were inserted as distributions including standard deviation and mean values, with nearly all collected data sets exhibiting normal distributions.

As outlined earlier, all datasets from the video captures and GIS maps were used to adjust the model in the most realistic fashion. The following parameters were included:

Number of truck inside the system

1.) Loading/unloading time

2.) Gravel, pavement, and highway travel distance

3.) Gravel, pavement, and highway average speed for full vehicles

4.) Gravel, pavement, and highway average speed for empty vehicles

5.) Random delay (due to unpredicted events)

It is important to note that randomly-distributed truck travel time was derived from the speed and distance distributions using appropriate equations, with normally-distributed and randomly-generated inputs. Travel time was derived using following formula:

$$Delay\ [minutes] = 60 * distance\ [kilometers]/speed[kmph]$$

The software basically changed input values each time new item representing a truck was generated. Travel speed was different for gravel and pavement surface types and for empty or full vehicle status. Accordingly, the model shown in Figure 27 utilized the above equation four times within each single cycle. Loading and unloading delay was measured on the field and presented in minutes, permitting direct inclusion in the model without additional data transformation. The data distributions associated with the input variables will be presented later in this paper. It is important to note that the data collection methods and input data accuracy have significant impacts on the model's credibility.
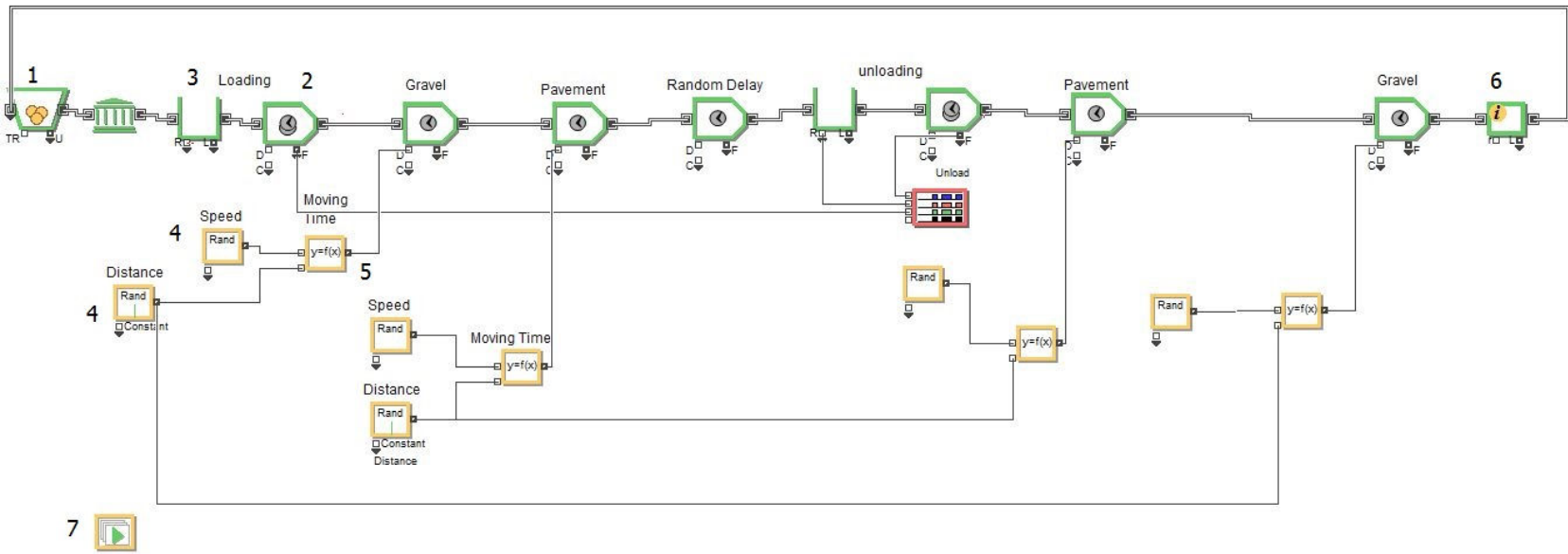
Figure 27 ExtendSim Model of a Single Transportation Cycle

ExtendSim model components are as follows:

1) **Resource component** generates the initial number of items representing biomass
   transportation vehicles. Once items are generated they stay in the system until the
   end of the modeling scenario.

2) **Process component** was used to represent activities such as trucks travelling on
   various road surfaces. Input D receives values from the formula component used to
   calculate travel time for given speed and distance distributions. An item
   representing a truck in the model will be delayed for the travel time input on
   connector D.

3) **Queue component** simulates queuing behavior of trucks that follows a first-in,
   first-out sorting method and is directly connected with loading activity. At the
   moment when a loader becomes available, an item leaves the queue component and
   starts being processed by the loading component.

4) **Random number component** generates random numbers conforming to the
   inserted data distribution. Almost all data distribution included in the corn-stover
   supply-chain modeling had normal distribution shape and was represented by
   average value and standard deviation.

5) **Equation component** calculates and outputs the results serving as inputs for the
   next component in the loop. For example, travel time is calculated using the
   following formula: Delay_min = Distance*60/Speed, where distance is a variable
   introduced as a distribution that takes on different values at different moments.

6) **Information component** keeps records about item arrival time and helps
   determine overall processing duration for each vehicle in the system.

7) **Scenario manager** is the component that configures and runs multiple simulation-model scenarios.

ExtendSim Scenario Manager Tool

Including the scenario manager in the modeling permits performing multiple simulations with different model factors that affect final model responses. By using this component it is possible to make assessment of influence of various factors on system productivity measured in terms of number of loads delivered. By including those factors in the model we allow the scenario manager to control components and to provide the full factorial number of inputs and thereby examine every combination of input factors. Using this tool it is also possible to choose several factor properties such as:

1.) Minimum and maximum value of the factor

2.) Step associated in creating combination (i.e., step =2 will generate 2,4,6 trucks in three different scenarios)

In the sample of model iterations presented below, modification of pavement distance is visible, but since there are more than 6 iterations for this specific model the other factors will be altered in the same manner. More details about the scenario manager setup will be provided in the results section.

Factor	Type	Levels	Values
Nr.Of Trucks	fixed	6	1,3,5,7,9,11
Nr. Of Loaders	fixed	2	1,2
Nr. Of Unloaders	fixed	2	1,2
Gravel Distance	fixed	2	1,3
Paved Distance	fixed	6	1,4,7,10,13,16
Mean/Median Loading Time	fixed	3	6,12,18
Mean/Median Unloading Time	fixed	3	3, 7.5,12

Table 8. Summary of the model iterations generated by scenario manager

The number of truck loads delivered in 10 hour working period was selected as a response. Using this dataset it was easy to derive the number of truck loads per hour and the number of loads/hour/truck for each possible scenario of the model.

In this research, the scenario manager was an excellent tool that allowed examination of the following factors in the system:

1) Effect of Distance and Number of Trucks on System Productivity

2) Effect of Distance and Number of Trucks on Road Vehicle Utilization

3) Effect of Number of Loaders on System Productivity

4) Effect of Number of Loaders on Road Vehicle Utilization

5) Effect of Loading Time on System Productivity

6) Effect of Loading Time on Road Vehicle Utilization

Results

Supply-Chain Productivity and Vehicle Utilization

The semi-Trailer (Flatbed) System was modeled taking into consideration the scenarios and system setup shown in Table 8. Each simulation case included ten modeling iterations, so each scenario outcome is an average outcome of ten modeling iterations in which each equipment combination was tested for 10 working hours.

Effect of Distance on Model Output

Altering road distance and number of trucks within a system can yield different values for system productivity (bales/hour). The modeling results are presented on the scatterplots below (Figures 28 and 29). It is important to note that system performance is presented both as the number of bales/hour/truck (direct indicator of truck utilization) and as the number of bales/hour (overall system performance, Figure 29). For paved distances less than 16 miles, one truck in the system exhibited optimal truck utilization, but overall system performance was significantly lower than that of the 3,5,7,9,and 11truck scenarios (Figure 28).
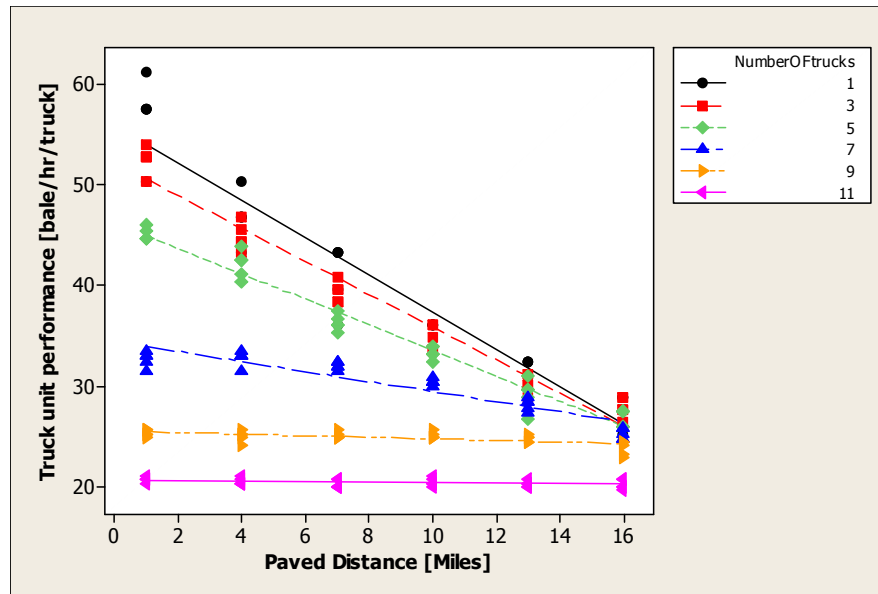
Figure 28. Effect of Distance and Number of Trucks

From Figure 29 it is obvious that using an 11-truck scenario had high overall system capacity (bales/hour) for all travel distance values. However, overall system performance in bales/hour is not the only indicator to be considered, and truck unit performance in bales/hour/truck is another important factor that should be included when comparing truck efficiencies. In cases when with 9 and 11 trucks in the system, a flat response of overall system performance with respect to distance will be achieved (Figure 29), and this is mainly due to increased system hauling capacity that is not adequately utilized. For distances less than 5 miles, seven, nine, and eleven trucks exhibit nearly similar productivity, i.e., we have more trucks than the transportation demand requires, with some of them are not properly utilized. In this case choosing seven trucks seems more reasonable. In the case where there are too many trucks in the system, they spend a significant amount of time queuing at the loading/unloading points. To improve truck utilization we simply need to decrease the number of trucks in the system (Figure 28) and,

even though we are decreasing overall capacity in bales/hour, we are increasing truck utilization. Therefore, a tradeoff for these two situations should be achieved by using a 7-truck operational setup.
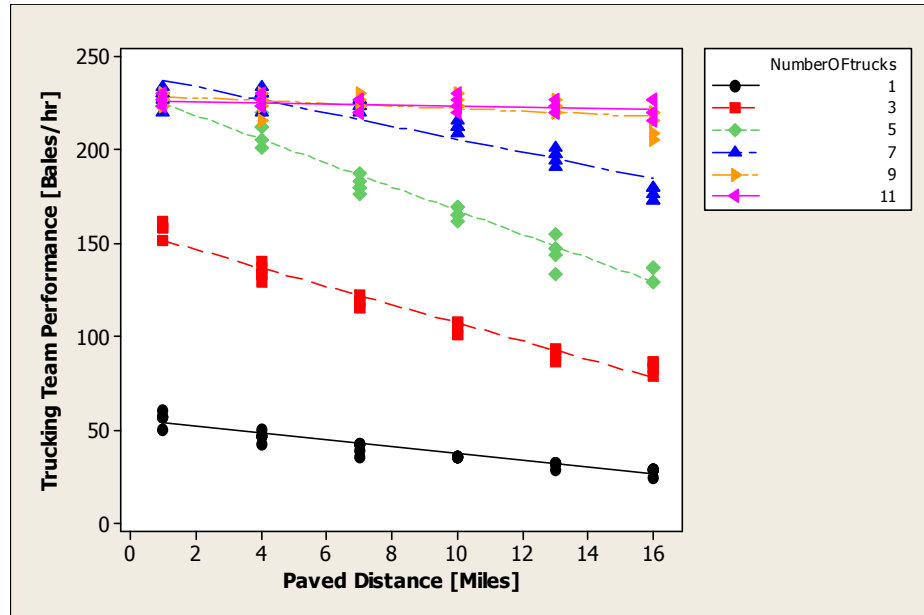

Figure 29. Overall System Performance (bales/hr)

Effect of Number of Loaders on Model Output

An increased number of loaders will result in decrease in truck delay at the loading/unloading points and an increase in truck utilization that may be significant depending on the number of trucks in the system. It can be inferred from Figure 30, that the more trucks in the system, the higher impact of a second loader. For one truck in the system, adding a second loader will produce only an insignificant change in truck utilization. On the other hand, in the case of 11 trucks, utilization will rise by almost 65 %. From the aspect of total system performance in bales/hour, for a one-truck system there is

no change in overall performance if an additional loader is employed. However, adding a second loader for the three or more truck scenario will result in significant system performance improvement. This is mainly due to elimination of truck dwelling time at the infield loading location. In these cases truck queuing time will be minimized or even totally eliminated during certain transportation cycles. In general, loading has greater influence on model outputs because loading time is significantly higher than unloading time. In some cases loading can even be 50% longer, so its influence is 50% higher than that of unloading time.

Adding a second loader has a positive influence on truck utilization, mainly due to loader idling in cases when no truck is present at the loading point or because a truck is being loaded by the second loader.
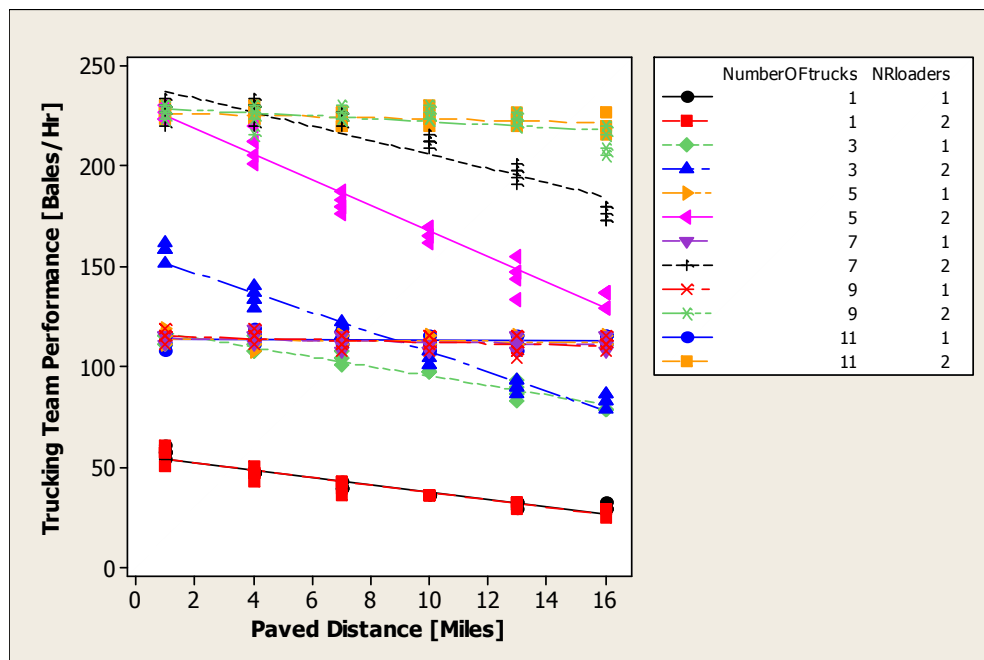

Figure 30. Impact of Number of Loaders on System Performance

In other words, by employing two loaders in the system, we improve truck utilization, but we also may decrease loader utilization. For one truck employing additional loader will not make any significant improvement. Using an additional unloader produces no significant improvement.

Effect of Loading Time on Model Output

It can be inferred from Figure 31 that reduction of loading time results in higher truck utilization. This influence is greater as the number of trucks increase.
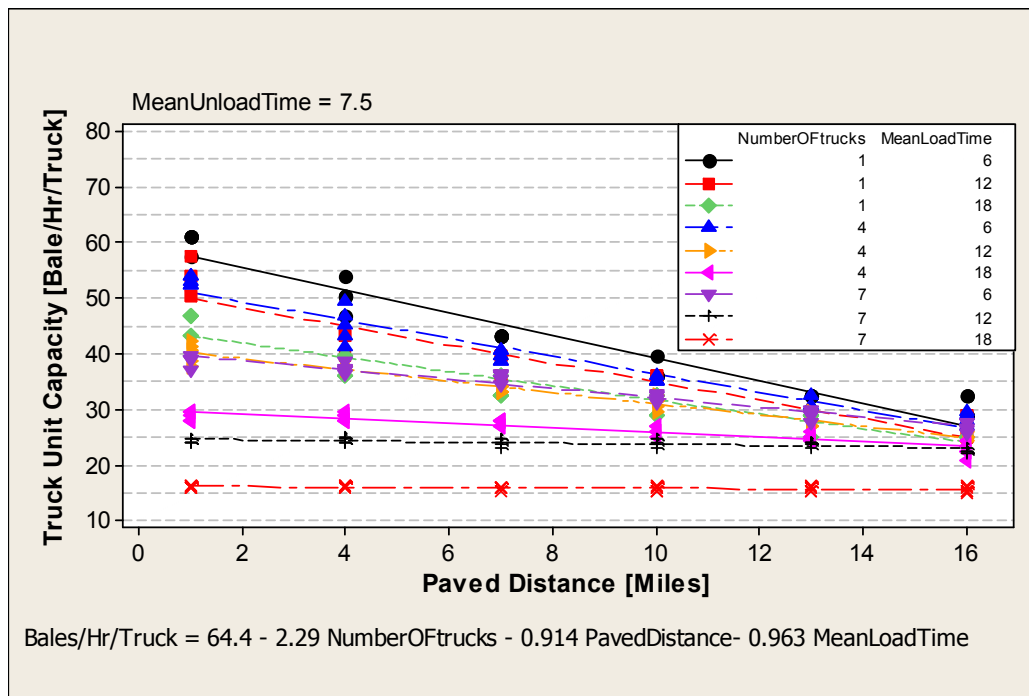

Figure 31. Influence of Loading/Unloading Time on Truck Utilization (Unit Capacity)

Figure 31 represents a regression equation describing effects of distance, loading time, and number of trucks on truck utilization:

Bales/Hr/Truck = 64.4-2.29 * NumberOFtrucks - 0.914 * PavedDistance -0.963 * MeanLoadTime

It can be inferred from the equation that truck utilization decreases with an increase in the number of trucks and loading time. Similarly, the total number of bales per hour increases as loading/unloading time diminishes (Figure 30). On the other hand, the influence of unloading time on system performance has a lower magnitude compared with the loading-time influence. As discussed earlier, this is mainly due to the nature of the unloading process, i.e., it is less time-consuming than loading. However, including more unloaders could be an appropriate solution in some cases. This might generally result in lower unloader utilization but also higher unloader availability, again possibly reducing truck queuing at the unloading point of the supply chain.

Effect of Road Surface Type

The majority of corn fields in Iowa are interconnected through a gravel road network. The main reason for use of gravel is low maintenance and construction costs. Gravel roads basically serve well in low traffic-volume conditions, but improper maintenance followed by intensive heavy vehicle movement can lead to very quick deterioration of a gravel road, especially in wet weather. In such cases average transportation speed is reduced and can significantly affect transportation productivity. Gravel road sections are the main avenues present at loading sites connecting corn fields with paved street networks and roads. Unloading sites are typically industrial-scale biomass storage facilities mainly located near paved-road construction to provide appropriate accessibility in all weather conditions year-round. During this study biomass transportation involved many fields and various gravel section lengths. Using GIS analysis,

gravel section length was measured and is presented on a boxplot (Figure 32). Since the central tendency is for gravel segment length to be about 2 miles and to range from 1 to 3 miles, it was reasonable to conduct sensitivity assessment for effect of gravel segment length on productivity using these numbers. Figure 45 shows transportation productivity for 1 and 3 miles of gravel distance. It can be inferred from this figure that no significant change in productivity was achieved for the chosen gravel road distance values. The reasons for such insignificant influence can most likely be explained by a combination of low overall gravel distance and dry and stable weather conditions during hauling.
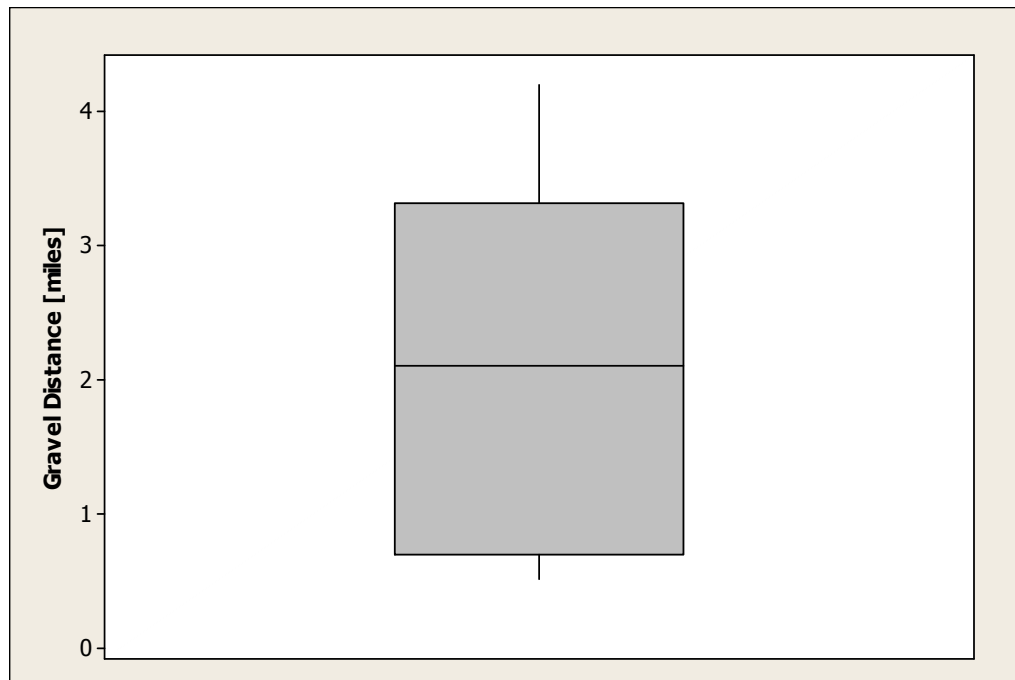

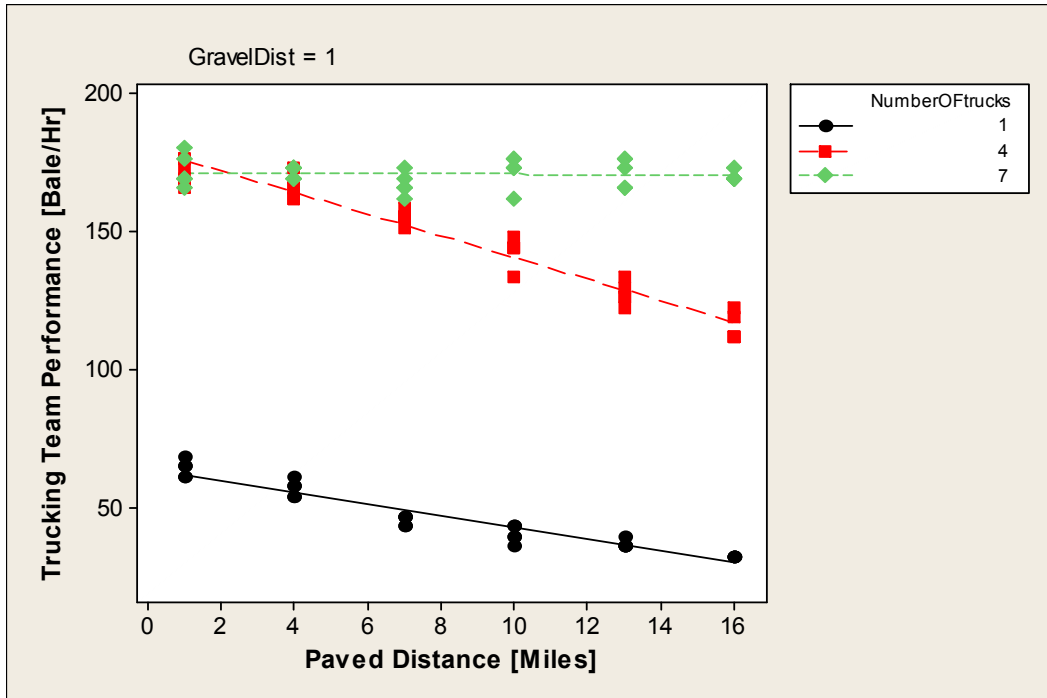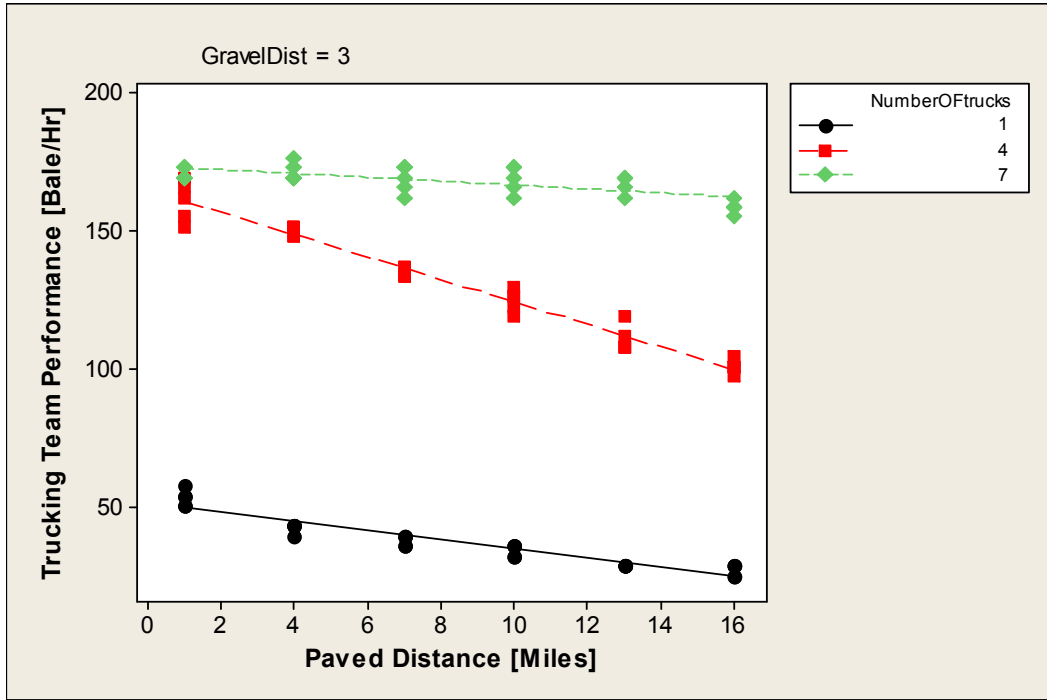**Figure 32 Box plot of gravel road section length**

Figure 33. Transportation performance with 3 and 1 mile gravel road section

However, there are some slight differences in productivity for the 1 and 3 mile gravel sections, and less gravel usage can yield better transportation productivity, especially in inconvenient weather conditions. Thus those fields that characterized with shorter gravel distances should probably be chosen during the decision-making process.

Number of Loaders and Utilization Impact

As discussed earlier, adding a second loader can make significant truck utilization improvements and decrease truck queuing times. Impact of a second loader is depicted on truck and loader utilization plot presented on Figure 34 below. It is obvious that additional loader decreases total truck queuing time and increases truck utilization (Figure 34).

- 1 Loader, 1 Unloader, 4 Trucks Operating 10 hours per day

Number of Loaders	1
Number of Unloaders	1
Loads/Truck/Day	24
Loads/Loader/Day	13

----- Queuing Activity
----- Loading Activity

- 2 Loader, 1 Unloaders, 4 Trucks Operating 10 hours per day

Number of Loaders	2
Number of Unloaders	1
Loads/Truck/Day	28
Loads/Loader/Day	9

----- Queuing Activity
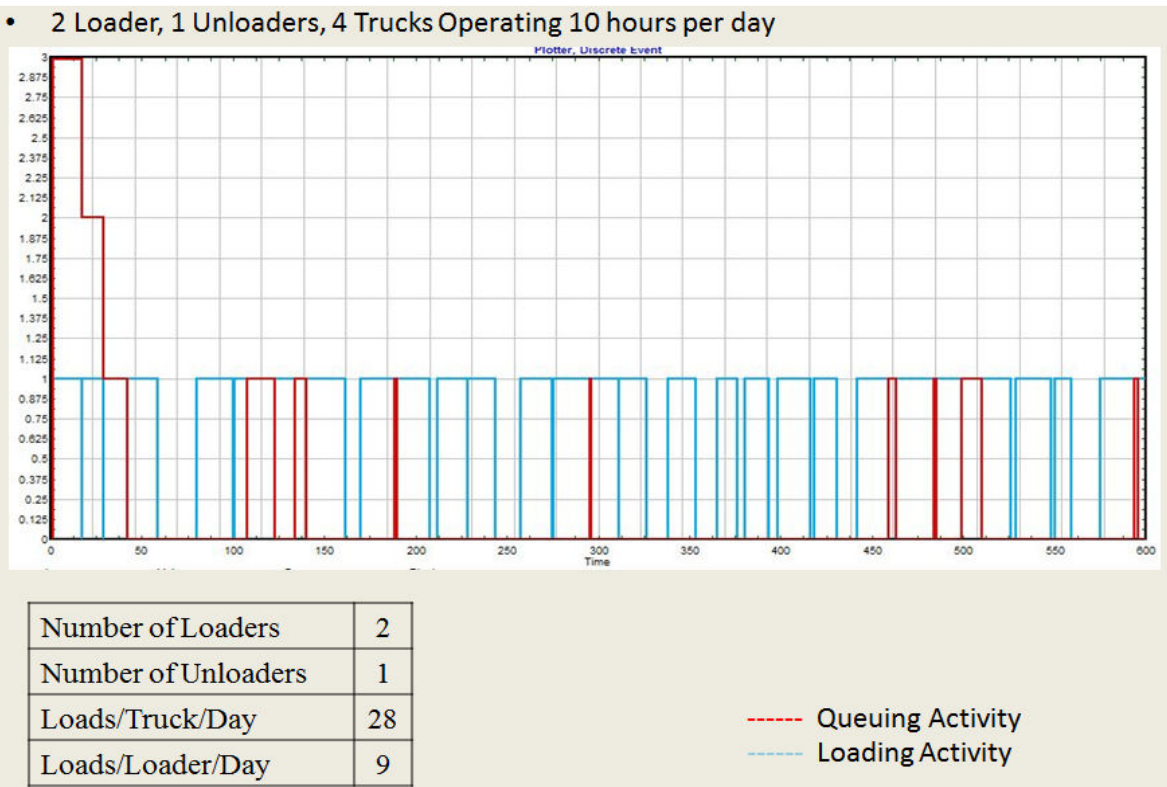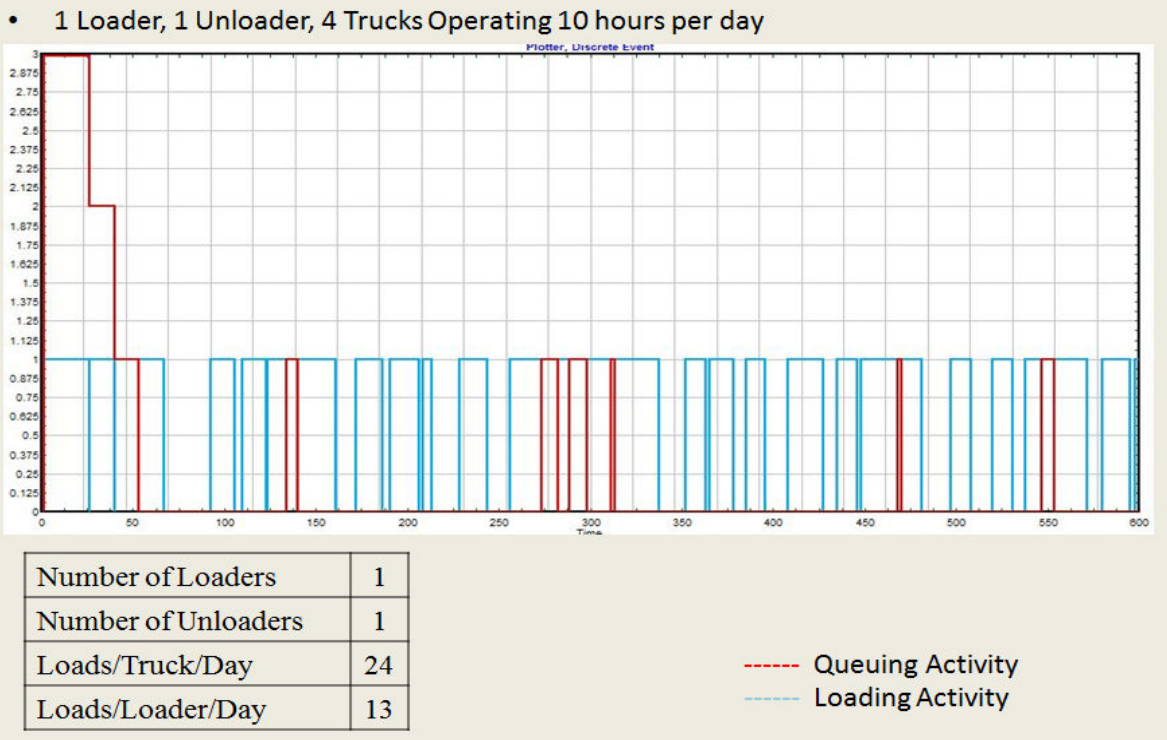----- Loading Activity

Figure 34 Truck and loader utilization plot (10 working hours)

Typical truck utilization improvements for different number of trucks are also

presented in Table 9 where fixed distance of 10 miles was assumed.

Truck Utilization - **tons/hr/truck**			
Number of Trucks	1	4	7
1 Loaders	20.42	19.24	11.23
2 Loaders	20.52	20.09	19.05
Utilization increase	0.1	0.85	7.82

Table 9 Impact of additional loader on truck utilization

Number of Vehicles and Transportation Unit Costs

As discussed earlier, the model developed for this study produced estimated

productivity rates in terms of bales per hour. To make a proper economical assessment of

certain research scenarios, costs were presented on an hourly basis. Figure 35 shows the

cost analysis framework. The various operational cost items, including machinery rental

expenses and supply chain personnel wages, have different impacts on total delivery costs.

To illustrate the different impacts, a sensitivity assessment was conducted with results are

presented in Figure 36. It is obvious from the figure that truck rental and trucking fuel

costs had the greatest impact on total delivery costs, so an optimization process that would

decrease the number of unnecessary trucks should yield the largest impact on total costs

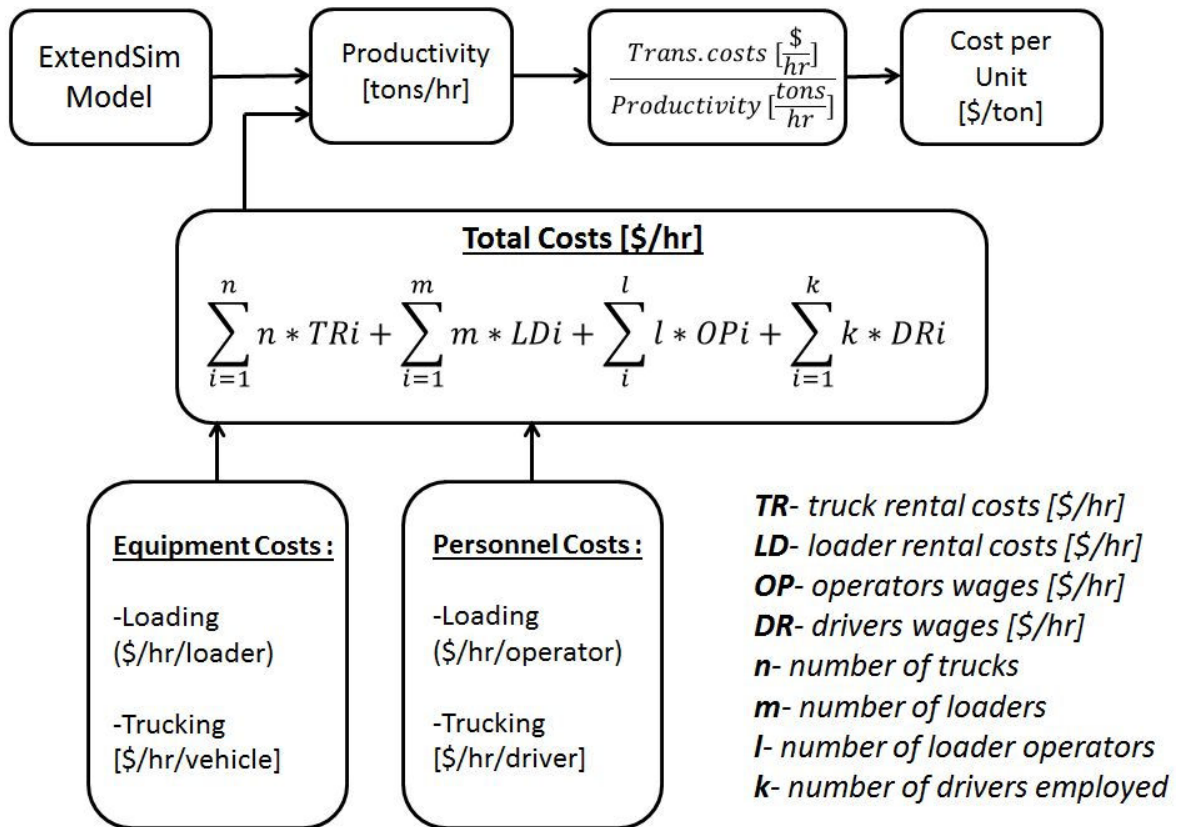and should be included in the optimization strategy.

Figure 35 Transportation Cost Analysis Framework

Expenses for the equipment and personnel are given in Table 10 below.

Cost Category	Unit	Values
Truck Rental+Fuel	$/hr	100
Payloader Rental+Fuel	$/hr	45
Loader Operator Wages	$/hr	18
Truck Driver Wages	$/hr	18

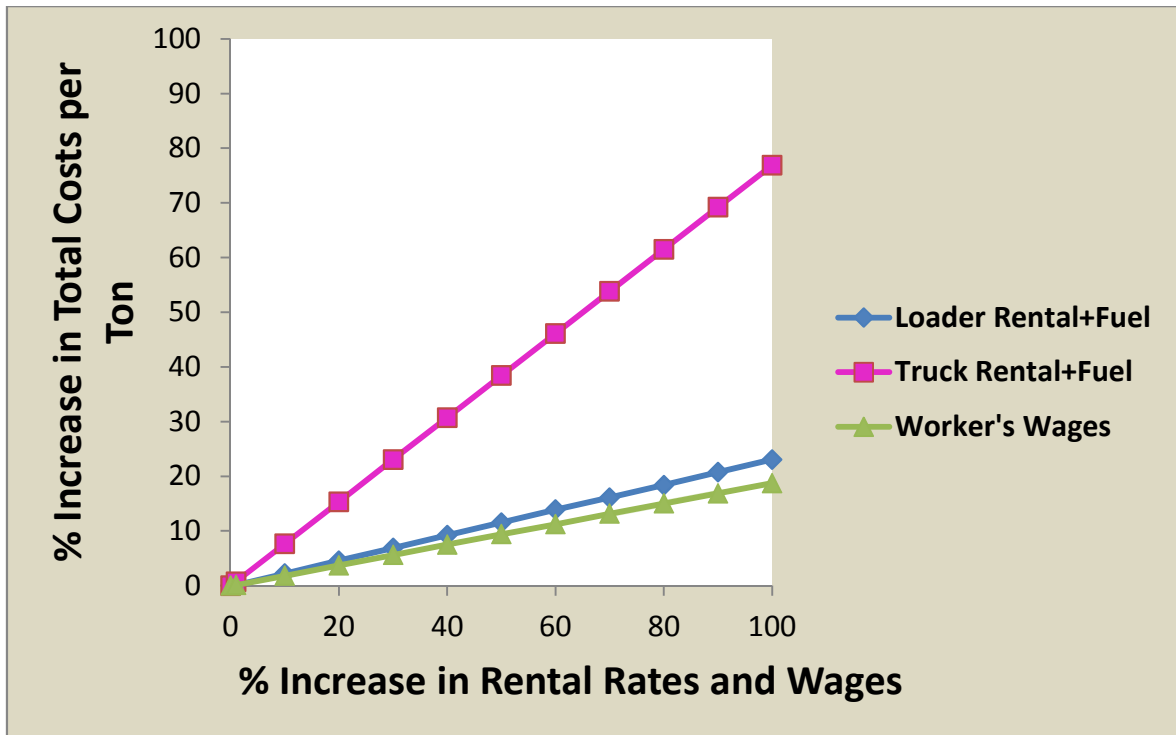**Table 10. Transportation Equipment and Personnel Expenses**

Figure 36. Impact of different input cost categories on the total delivery costs

The final result is expressed as cost per dry ton for each examined scenario. As described earlier, the model utilizes a scenario manager that allows development of full-factorial assessment, producing iterations with all possible factor combinations with each combination tested for 10 working hours per day.

In all circumstances, transportation productivity decreases with distance traveled. One way to maintain required transportation productivity is to employ additional vehicles to increase the total number of delivered cargo units per hour, day, or month. However, the number of vehicles and the distances affect transportation unit costs as well, and employing too many vehicles will result in low vehicle utilization and increased total per-ton cost in general.
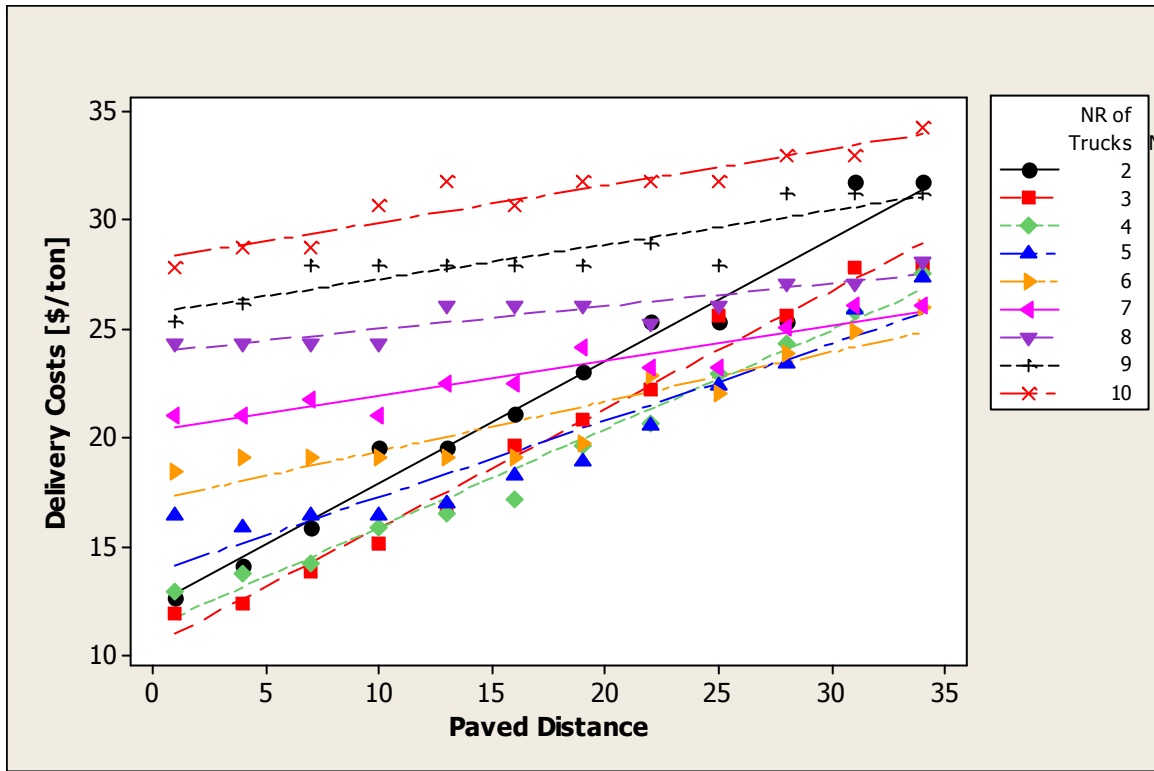
Figure 37. Costs per ton as a function of the distance and number of trucks employed

From Figure 37 it is obvious that unit costs in dollars per ton increase with the number of trucks. However, it is important to understand that transportation capacity in this case is rising as well, and that transportation demand and transportation time window are the main factors that should be used in selecting the desired number of vehicles. It can be also inferred from Figure 37 that certain minimal costs also depend on distance. For example, with one loader on each side and distances between one and ten miles, minimal costs will be achieved if three trucks are used, and distances between ten and twenty miles will achieve minimal costs using four or five trucks, etc.

It is important to point out that transportation costs per unit rise with the number of trucks due to limited number of loading slots. With a large number of trucks and limited

vehicle loading slots, vehicle utilization can significantly decrease. In such a case the number of delivered loads will be reduced and operational costs will be higher since more equipment is employed. Figure 38 illustrates different unit-cost values as a function of distance while taking into consideration different numbers of trucks and for one loader on each side. In the upper graph a truck utilization plot is presented. It is obvious from these two graphs that poor utilization yields high unit cost. It can be also inferred from the graph that, for distances between 1 and 15 miles, the lowest unit cost will be achieved using 3 trucks. Transportation costs range from 4 to 13 dollars per dry ton. However, for distances between 15 and 30 miles the lowest unit costs were achieved using four trucks. For distances between 30 and 35 miles six trucks achieved the lowest unit cost. The cost range was 13-17 dollars per ton and 17-19 dollars per ton, respectively, for the described distances. Distances over 35 miles were not considered in this step, since distance distribution rarely exceeded this value during the data collection process (Figure 13).
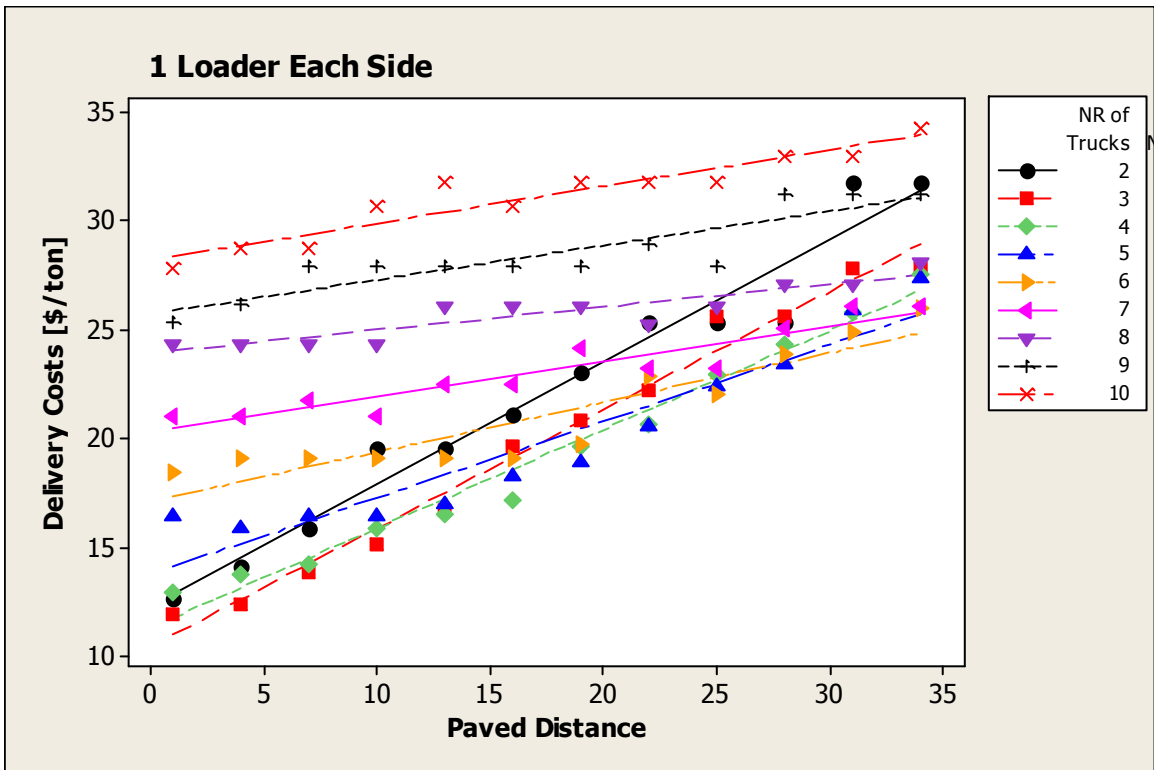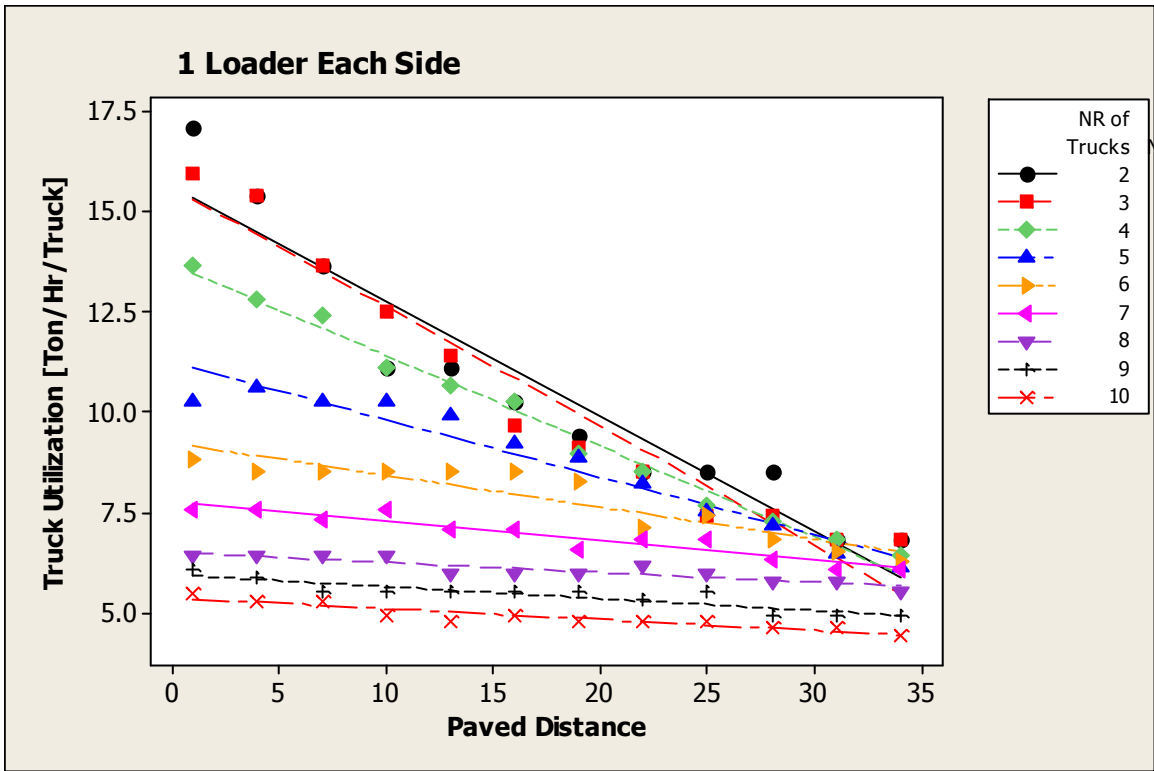
Figure 38. Utilization Plot and Transportation Costs over the Distance

The highest cost values were achieved using 10 trucks, which was expected since queuing delays decreased system productivity. Each hour of trucking will generate costs, and transportation management should pay attention to truck queuing effects. Large truck queuing delays caused by unbalanced trucking capacity will result in low vehicle utilization values (loads/truck/hr). Employment of an additional loader will positively impact unit costs for all equipment setup combinations by reducing truck queuing times and increasing the number of cargo units delivered
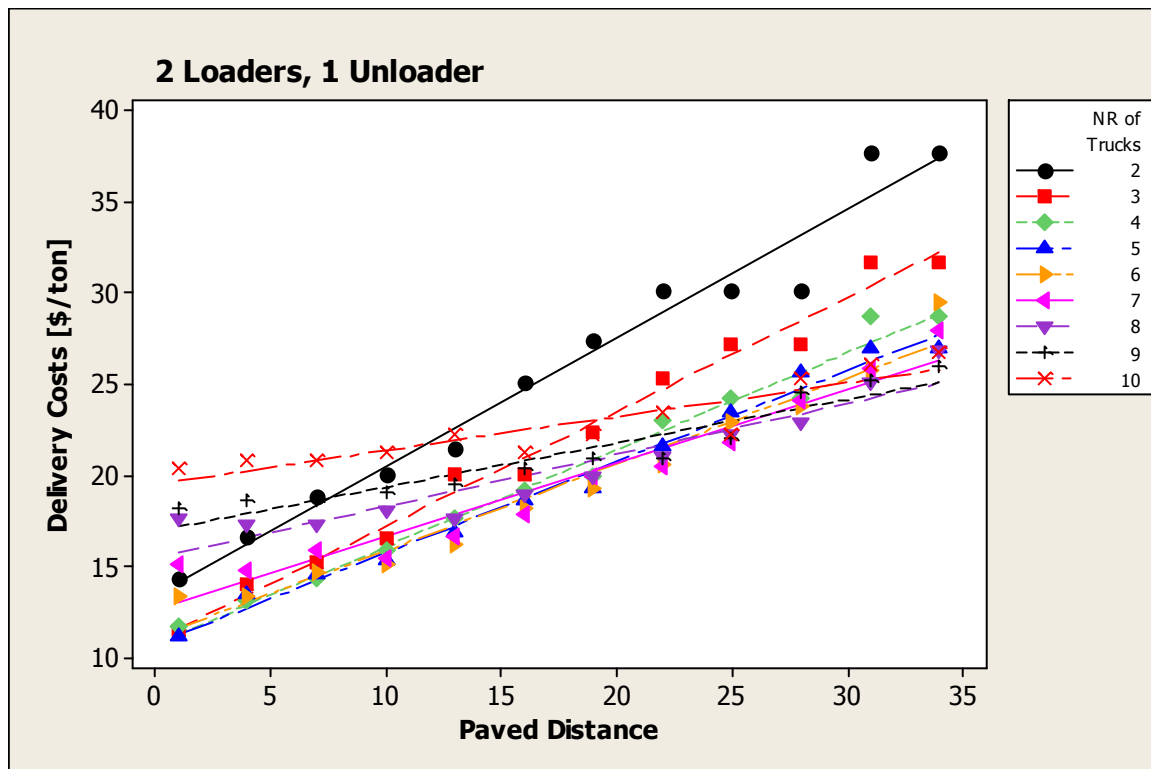

Figure 39. Transportation Costs Over the Distance and Number of Trucks with Additional Loader

Adding a second loader decreased unit costs in general. In particular, for distances between 1 and 15 miles these costs are likely to range between 6-13 dollars per ton if 4 trucks are

employed. For distances between 15 and 35 miles the lowest unit cost values ranging from
13-17 dollars per ton will be achieved using 7 trucks.
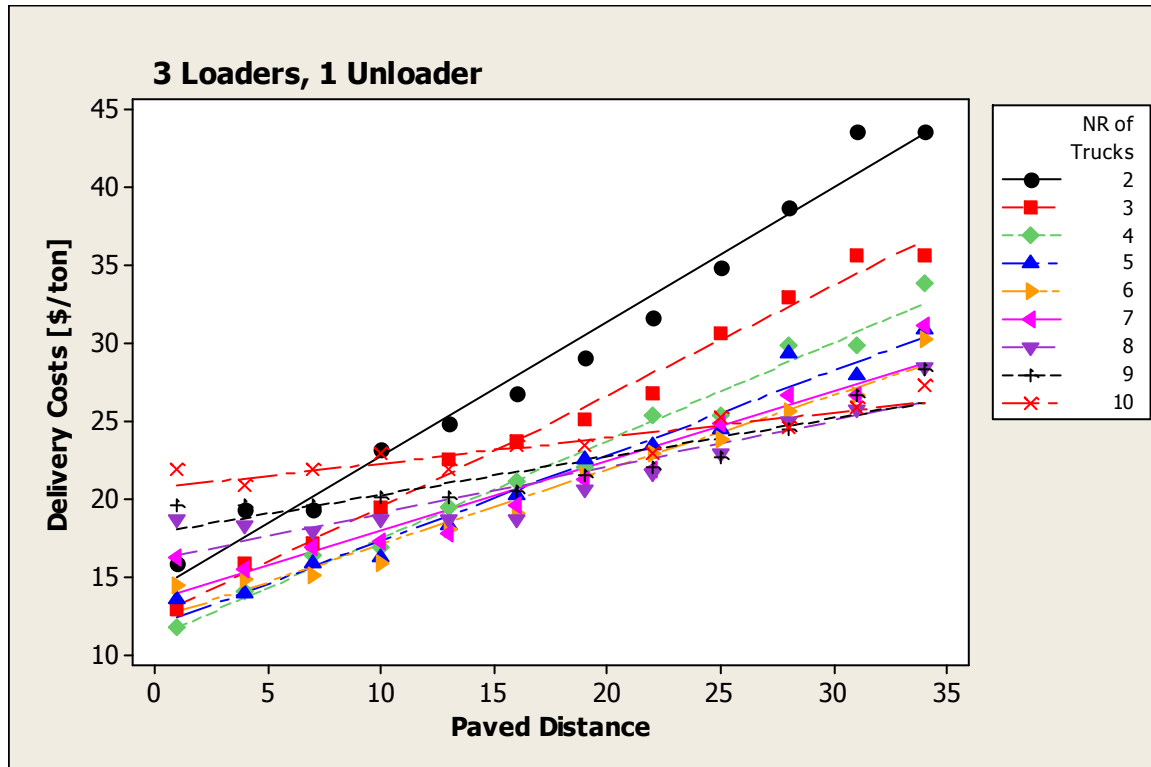
Figure 40. Transportation Costs Over the Distance and Number of Trucks with Three Loaders

An operational pattern that includes three loaders within a 35-mile hauling radius is
presented in Figure 40. The lowest possible per-ton cost is achieved with 5 trucks and three
loaders if the hauling radius is less than 15 miles. Costs in this case may range from 8 to 13
dollars per dry ton. Distances above 15 miles will demand 7 or 8 trucks and costs are likely
to range from 13 to 18.5 dollars per dry ton.

Seasonal Decision-Making Process

It should be pointed out that the lowest possible per ton cost is not the only factor determining the most desirable equipment setup. Transportation demand is the key essential factor in transportation decision-making. The optimum number of vehicles and handling-equipment units will be a function of the bale production dynamics and the transportation-time window. To illustrate one transportation decision-making process, one seasonal decision-making example will be presented. This example assumes a single storage location and a 10-mile corn-stover collection radius. Figure 41 shows a typical seasonal bale production trend. The blue curve represents the cumulative number of bales stored at the edge of fields within the hauling radius. The number of bales produced is represented by an empirical curve based on the bale production dynamics of 2011. The cumulative number of bales produced is compared with the cumulative number in storage. This latter value was estimated using a modeling approach described in this study, where transportation productivity in bales per day was derived assuming 10 working hours per day.

The seasonal example also assumed following parameter values:

Factor	Type	Levels	Values
NumberOFtrucks	fixed	3	1, 4, 7
NRloaders	fixed	2	1, 2
NRunloaders	fixed	1	1
GravelDist	fixed	1	3
PavedDistance	fixed	1	10
MeanLoadTime	fixed	1	18
MeanUnloadTime	fixed	1	12.0

Table 4 Factors and Levels for the Modeling

The red curve on the graph represents the number of bales in storage or the cumulative number of bales transported. It is obvious that the time lag between number of bales produced and the number transported increased over the time. This typical example describes the nature of the harvesting process in terms of a tendency to increase in number of fields harvested over time. The transportation decision-making process should therefore include close monitoring and future transportation-demand forecasting. In this case study, the initial number of vehicles employed was four (Figure 41) and the system encountered a so-called cold start

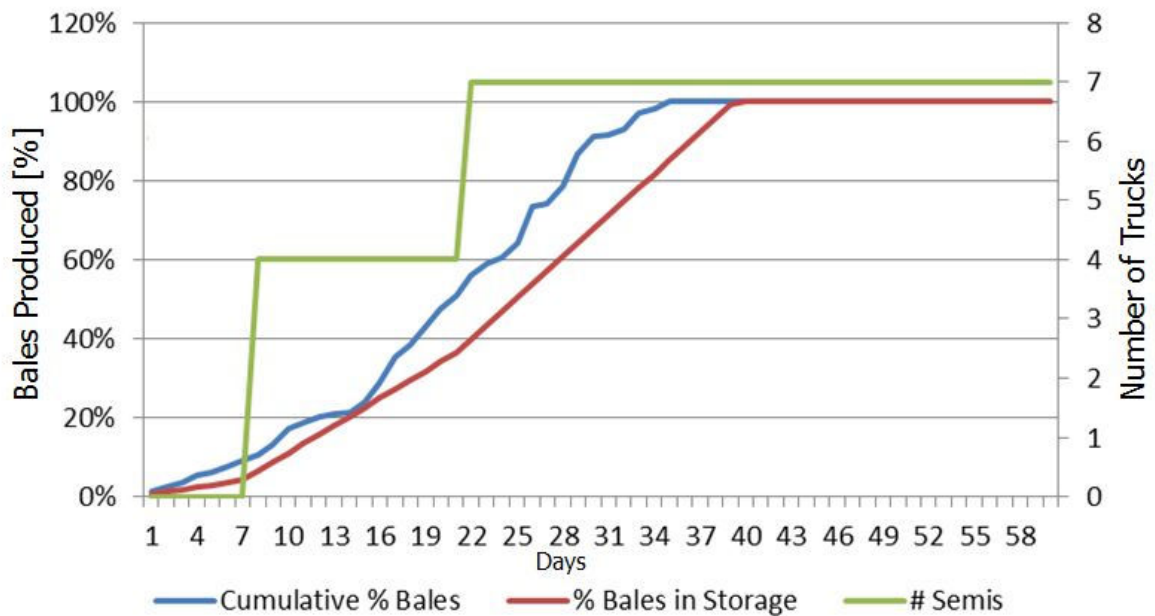**Figure 41 Seasonal Case Study for the Single Storage and 10 Miles Collection Radius**

during the first week, so it seemed reasonable to begin the hauling process in the second week instead. As mentioned above, for a hauling radius below 15 miles it was recommended to employ four trucks to obtain minimal per-ton cost. Even with an increased number of trucks the time lag between bale production and bale transportation

increases, demanding more vehicles and higher transportation productivity. It can be inferred from the Figure 38 that beside four trucks, next acceptable scenario regarding per ton cost can be 5 or 7 trucks. With seven trucks, the supply chain finished its hauling process and secured all produced bales in 45 days. This seasonal example illustrates the decision-making process taking into consideration the modeling approach and recommended supply-chain organization patterns. Minimal cost is not the only factor that will determine establishment of a given machinery setup; another very important factor is transportation demand. Taken together those two factors may produce a useful decision-making tool and implement the supply chain in a more efficient manner.

The following recommendation matrix was developed for the purposes of discussing the above seasonal example, but such a matrix can be developed for any transportation scenario using different transportation parameters.

Week	1st	2nd	3rd	4th	5th
Number of Trucks	0	4	4	7	7
Number of Loaders	0	2	2	2	2
Number of Unloaders	0	1	1	1	1
Expected $/ton	0	11.5	11.5	16.25	16.25

Table 11 Recommended Transportation Setup from the Aspect of Transportation Demand and Costs

Table 11 gives recommended truck-loader combinations that can satisfy transportation demand while producing the lowest possible costs. As discussed before, it is important to increase transportation capacity as the bale production trend starts moving toward its peak and this must be done by selecting a higher-capacity setup that can satisfy demand while maintaining costs at the lowest possible level. Otherwise the transportation

system will not be able to transfer all bales to storage locations before severe weather conditions occur. All the methodology from this case study can be applied to any other specific transportation problem using appropriately different supply-chain parameters. It is necessary to conduct close monitoring of transportation activities and increase transportation capacity to allow for unpredicted interruptions.

Conclusion

As with any supply chain, the corn-stover supply chain must satisfy one major requirement. It must provide a sufficient number of transportation units within a time-limited period while achieving minimal operating costs. Discrete modeling can be used to make appropriate assessment of different transportation scenarios by considering factors such as average travel distance, road surface, number of vehicles, and needed handling equipment. Full factorial assessment provides an opportunity to examine every possible combination of included factors.

Distance is one of the factors affecting transportation productivity in the following manner. Long travel distances demand a higher number of vehicles to satisfy the desired transportation demand, and this of course affects overall delivery costs. One indicator that supports decision-making in specific transportation scenarios is transportation productivity measured in bales/hr, but overall system performance in bales/hour is not the only indicator that should be considered. Truck utilization in bales/hour/truck is another important factor to be included when it comes to selection of the most efficient and economically-acceptable scenario.

Another very important factor affecting supply-chain optimization is the number of loading and unloading channels. This factor, along with number of vehicles employed, has a direct impact on vehicle utilization. A large number of vehicles supported by a low number of loading and unloading channels will result in poor vehicle utilization and high operational costs.

Road surfaces like gravel tend to decrease transportation productivity rates. The majority of cornfields in Iowa are interconnected via a gravel road network and, for the corn stover supply chain in this study, the average gravel distance for each transportation cycle was about 2 miles with a range of from 1 to 4 miles. Gravel distances in such a narrow range insignificantly affect system productivity.

Transportation costs increase with the number of trucks employed. For example, 10 trucks operating in a distance range of from 1 to 35 miles with one loader at each end are likely to achieve transportation costs ranging from 21 to 25 dollars per dry ton while maintaining transportation productivity ranging roughly from 70 to 23 tons per hour. The same costs for a five-truck system might range from roughly 10 to 18 dollars per ton, but productivity rates would be lower and would roughly range from 5 to 23 tons per hour depending on distance.

Truck utilization has a strong impact on unit costs measured in dollars per bale. Poor vehicle utilization and low transportation productivity will require more working hours than those needed in an adequately adjusted transportation system. More overall working hours means more expenditure for personnel wages and equipment rental, so appropriate equipment utilization tends to decrease overall costs. Truck utilization increases with the number of loaders employed; therefore for the case described above in

which 10 trucks are operating within a distance range of 1 to 35 miles, providing an additional loader could decrease transportation costs from 14 to 18 dollars per dry ton while achieving productivity rates up to 105 tons per hour based on a 10-hour shift. When dealing with an organization's decision-making process, it is important to understand the concept of transportation demand and unit costs. The principal transportation task is to deliver a certain number of transportation units to the storage location within a limited time window. Failure to organize transportation in a timely fashion may result in exposure of corn-stover bales to severe weather conditions. Certain organizational patterns might achieve low operational costs in dollars per hour but might not provide sufficient transportation productivity. On the other hand, highly-productive scenarios might be unacceptable from the aspect of operational costs. An optimal scenario must provide sufficient productivity to satisfy proposed demand while achieving the lowest possible costs. Transportation activities must be closely monitored during the harvest season to increase transportation productivity in unpredicted situations that could cause interruptions.

REFERENCES

Arns, M., M. Fischer, P. Kemper and C. Tepper (2002). "Supply Chain Modelling and Its Analytical Evaluation." The Journal of the Operational Research Society **53**(8): 885-894.

Beamon, B. M. (1999). "Measuring supply chain performance." International journal of operations & production management **19**(3): 275.

Darr, M. J. and A. Shah (2012). "Biomass storage: an update on industrial solutions for baled biomass feedstocks." Biofuels **3**(3): 321-332.

Dukulis, I., G. Birzietis and D. Kanaska (2008). "Optimization Models for Biofuel Logistic System." Engineering for Rural Development - International Scientific Conference ;2008.

EISA (2007). Energy Independence and Security Act of 2007. t. U. S. Congess.

Ingallis, R. G. (1998). The value of simulation in modeling supply chains. Simulation Conference Proceedings, 1998. Winter.

Kenedy, M. (2002). "The GlobalPositioning System and GIS." (CRC Press): 345.

Lau, M. W. and B. E. Dale (2009). "Cellulosic ethanol production from AFEX-treated corn stover using Saccharomyces cerevisiae 424A(LNH-ST)." Proceedings of the National Academy of Sciences **106**(5): 1368-1373.

Lee, Y. H., M. K. Cho, S. J. Kim and Y. B. Kim (2002). "Supply chain simulation with discrete–continuous combined modeling." Computers & Industrial Engineering **43**(1–2): 375-392.

Searcy, E., P. Flynn, E. Ghafoori and A. Kumar (2007). The Relative Cost of Biomass Energy Transport. <u>Applied Biochemistry and Biotecnology</u>. J. Mielenz, K. T. Klasson, W. Adney and J. McMillan, Humana Press**: 639-652.**

CHAPTER 5. GENERAL CONCLUSION

General Discussion

Stable, functional, and efficient bioethanol production systems on the national level must emphasize solutions of feedstock availability and transportation problems. With the growing demand for corn stover transportation, the supply chain planning must put emphasis on equipement utilization, while meeting transportation demand and time window requrements.

In Capter 3, *Using GIS and Intelligent Transportation Tools for Biomass Transportation Productivity Assessment,* a detailed report on a recent analysis of production-scale biomass transportation was provided. For that purpose intensive Geographic Information Systems (GIS) tracking and video capture of the loading, securement, hauling, and unloading events were collected and the results were summarized.

Chapter 4, *Corn Stover Supply Chain Optimization and Modeling*, presented specific results including: metrics for measuring supply chain efficiency, current capability of biomass supply chains, and sensitivity analysis to improvements in future supply chains. Collected data from Chapter 3 was utilized to conduct proper discrete modeling of the corn stover supply chain which allowed proper assessment of the supply-chain system performance. For a typical corn-stover biomass supply chain, baled corn stover must be transported in two phases, first from the field to a storage site and then from the storage site to the biorefinery. This organization pattern typically requires satellite storage

locations (SSL) to be formed within corn stover collection radius. Average SSL collection radius, determined during the study was approximately 10 miles. To properly satisfy all necessary optimization requirements of such SSL unit, it is recommended to employ four truck, two loaders and one unloader during first three weeks of the bale hauling process, when transportation demand is typically lower. In the fourth week, bale production trend is likely to start moving toward its peak. It is recommended to increase transportation capacity at this point, and employ up to seven trucks supported by 2 loaders and one unloader, until the end of hauling season. From the aspect of transportation costs, such organization should achieve 11.5 $/ton during first three weeks and 16.25 $/ton during the season peak. It is also necessary to conduct close monitoring of transportation activities and increase transportation capacity to allow for unpredicted interruptions.

A variety equipment to handle bales currently exists. During the study a telehandler-mounted three-bale spear and squeeze systems were examined. The difference in performance for the two systems is insignificant, and the whole loading process is likely to range from 18 to 24 minutes roughly. It is recommended to use Automatic Load Securement System (ALSS) that by elimination of strapping procedures achieved lower loading delays taking approximately 13 minutes, on average.

In addition to that it must be outlined that closely monitoring of transportation is highly recommended. The monitoring must include several activities such as: vehicle queuing effect observation, overall time at loading/unloading sites, loading/unloading delay and system performance estimation. Also, appropriate determination of optimal

number of loaders and vehicles to increase vehicle utilization should be achieved using

software simulation

Such methodology was presented in this thesis, and for typical satellite storage

location with average transportation distance of 10 miles, minimal costs can be achieved

using bale hauling team consisted of 4 semi-trucks, 2 loaders and 1 unloader.

It is essential to understand that supply chain optimization process does not provide

a permanent solution, since bale production and transportation dynamics may differ from

one year to another. However, supply chain optimization can be achieved using

methodology recommended in this research, while conducting appropriate monitoring and

future transportation-demand forecasting.

ACKNOWLEDGEMENT

I would like to express my deepest appreciation to my major professor Dr. Matthew Darr who provided me the possibility to conduct this research. Dr. Darr provided all necessary help in methodology development, result analysis, writing and editing assistance. Without his guidance and persistent help this thesis would not have been possible.

Special thanks for Iowa State University's HST Consortium (ADM and ConocoPhillips) who provided financial support for this research.

I would also like to thank my committee members, Dr. Konstantina Gkritza and Dr. Stuart Birrell for their suggestions and advices, and my research group members Ajay Shah and Keith Webster for their help and support during the study.

My family has been an irreplaceable support throughout my graduate study. Thank you for encouragement and help.