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Modeling of Biorefinery Supply Chain Economic Performance with Discrete Event Simulation

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MODELING OF BIOREFINERY SUPPLY CHAIN ECONOMIC PERFORMANCE
WITH DISCRETE EVENT SIMULATION

THESIS

A thesis submitted in partial fulfillment of the
requirements for the degree of Master of Science in Manufacturing
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By

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Lexington, Kentucky

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ABSTRACT OF THESIS

MODELING OF BIOREFINERY SUPPLY CHAIN ECONOMIC PERFORMANCE WITH DISCRETE EVENT SIMULATION

As competition for fossil fuels accelerates, alternative sources of chemicals, fuels, and energy production become more appealing to researchers and the layman. Among the candidates to fill this growing niche is lignocellulosic biomass. Many researchers have examined supply chain design and optimization for biofuel and bioenergy production throughout the years. However, these models often fail to capture the variability and uncertainty inherent to the biomass supply chain. Multiple factors with high degrees of stochasticity can have major impacts on the performance of a biorefinery: weather, biomass quality, feedstock availability, and market demand for products are just a few. To begin to address this issue, a discrete event simulation model has been developed to examine the economic performance of a region specific, multifeedstock biorefinery supply chain. Probability distributions developed for product demand and feedstock supply begin to address the random nature of the supply chain. Model development is discussed in the context of a multidisciplinary framework for biorefinery supply chain design. A case study, sensitivity analysis, and scenario analysis, are utilized to examine the capabilities of the model.

KEYWORDS: Biomass Supply Chain, Biofuel, Discrete Event Simulation, Multidisciplinary, Uncertainty.

Joseph Soren Amundson

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Dedicated to my family and friends

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1 INTRODUCTION

1.1 Background Information

As fossil resources for the production of transportation fuels and energy have become ever more scarce due to dwindling supply, inefficient use, and increasing demand, interest in renewable and alternative sources of raw materials for these purposes has steadily grown. One technologically viable option for substitution in this regard has proven to be biomass. The ability to produce biofuels and other products utilizing various biomass feedstocks and chemical processes has been demonstrated (Tripp et al, 2009). Heat and electricity, transportation fuels, specialty chemicals, and other synthetic materials traditionally derived from fossil fuels can technically be developed from various biomass feedstocks.

Biofuels can broadly be categorized as first-generation, second-generation, or third-generation based on feedstock inputs. First generation techniques utilize well-established technologies to convert seeds, grains, or whole plants to biofuels. The feedstocks are typically derived from food products. Second generation biofuels are produced using thermochemical pathways or fermentation with non-food source feedstocks. In addition to agricultural and forestry residues, potential biomass resources include all plant-derived materials including starches, sugars, and oils. Additionally, animal waste, urban-wood residues, industrial process residues, and municipal solid waste could be considered potential feedstocks (An et al, 2011; Perlack et al, 2005). Third generation biofuels are produced from algae or seaweed. Here, the biomass is harvested from nature or gown for use as feedstock in chemical conversion processes (Nigam and Singh, 2011). In general, third generation biofuels are not considered relevant in the marketplace until 2050 due to the state of technology development (Bringezu et al, 2009). What's more, researchers have shown that, from a lifecycle perspective, the environmental impact of these alternative products can be significantly less than fossil fuels. Mu et al. (2010) point out that recent LCA studies have consistently shown possible greenhouse gas emission reductions of greater than 50% by utilizing biochemical or thermochemical means to produce fuels from biomass.

In addition to scientific support, significant political will has been garnered in favor of expanding the use of biofuels around the globe. The European Union has instituted minimum biofuel content legislation that will take full effect by 2020. With the passage of Directive 2003/30/CE, the member states have mandated that transportation fuels will contain 10% biofuel by that time (Londo et al., 2010). Similarly, Argentina mandates a minimum content of biofuels in gasoline and diesel (Mele et al., 2011). Increasingly, nations all around the world are setting goals for increased use of bioenergy (Olsson, 2007). Notably, the USA has taken significant measures to increase biofuel production and consumption nationally. The Renewable Fuels Standard (RFS), established in 2005 (Public Law 109-58, 2005), created a volumetric consumption mandate for biofuels for the first time. Subsequently, in 2007, this historic standard was expanded by the passage of the Energy Independence and Security Act (EISA) of 2007 (Public Law 110-140, 2007). This legislation, which more than doubles the requirements set forth with the RFS, establishes the RFS2. Optimistically, legislators mandated up to 36 billion gallons of biofuels by 2022 with 21 billion gallons made up of advanced biofuel derived from sources other than those traditionally used to produce ethanol. Of these 21 billion gallons, 16 billion gallons should be comprised of fuels derived from cellulose, hemi-cellulose, or lignin of renewable biomass that has lifecycle greenhouse gas emissions that are at least 60% lower than the baseline established in 2005 (Biotechnology Industrial Organization, 2011). This planned increase in consumption is illustrated in Figure 1-1.

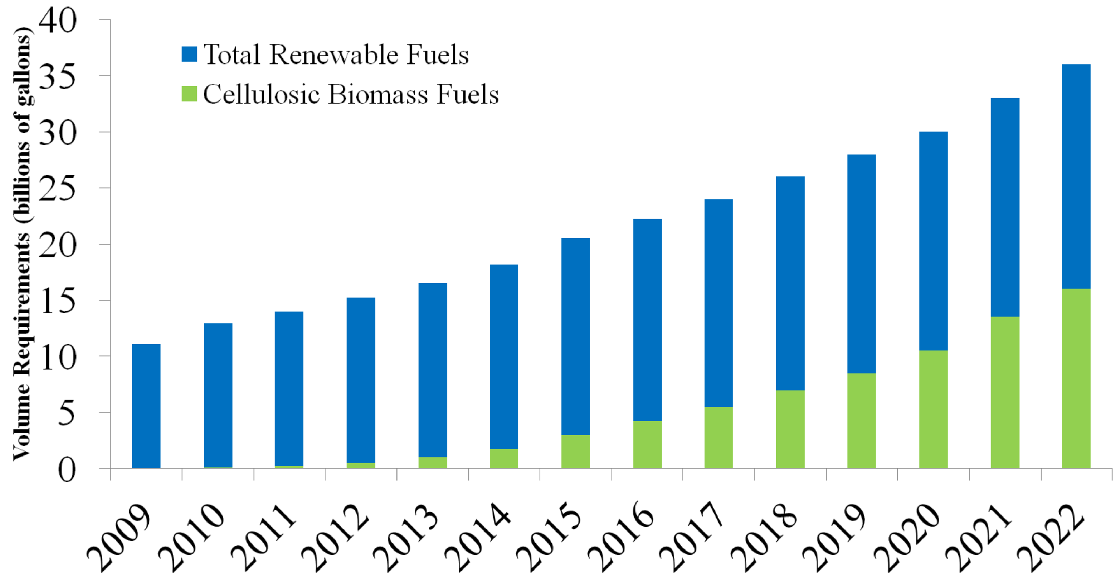


Figure 1-1 RFS2 Consumption Mandate (Biotechnology, 2011)

At a more local level, many state governments in the USA have instituted various regulation regimes and incentive programs for biofuel production and consumption. For example, perhaps accelerated recently in response to the passage of the RFS and, subsequently, the RFS2 on the national level, all states have taken the initiative to create utilization policies for woody biomass. Becker and Lee (2008) compiled a comprehensive collection of state policies related to biofuel, energy efficiency, and energy production from biomass based sources. The national distribution of policies, as well as the date of the most recently enacted policy can be seen in Table 1-1. The authors of the sampled study categorized state level incentive policies in the following way: tax incentives including exemptions, deductions, credits, or reductions of sales, corporate/production, personal, and/or property taxes; subsidies including cost sharing, rebate, and grant programs; rules and regulations including renewable energy and fuel standards and certification requirements; education and consultation including research initiatives or training to enhance biomass technical expertise; and financing and contracting including business recruitment, issuing bonds, making low/no interest loans available, and procurement and contracting to require biomass product use in certain activities. From the table it is clear that in recent years interest in providing incentives for business investment in biotechnology for fuel and energy production has increased.

Although the EPA has lowered the fuel standard for cellulosic biofuels on multiple occasions (ultimately decreasing the production milestones from a required 500 million gallons in 2012 to 8.65 million gallons in 2012 (Bracmort, 2012)), the existence of this type of legislation globally indicates a need for expanded biofuel production capacity. In fact the United States Energy Information Administration predicts the domestic production of ethanol and biodiesel together to increase by at least around 20% by 2015 and by at least 64% by 2035 (US EIA, 2012a). Assuming that market pressures and political support continue to increase together, the need for expanded biorefinery and bioenergy production capacity will doubtless become an issue to be dealt with.

Despite the proven chemistry, political support, and potential environmental benefits biomass currently accounts for only a fraction of the energy production and transportation fuel consumption in the United States. Figure 1-2 illustrates the use discrepancy by comparing annual consumption of gasoline, fuel ethanol, and biodiesel from 2009 projected into 2014. The apparent discrepancy between technological capability and technology implementation is thus revealed. Bio-based sources of transportation fuels have clearly not become competitive alternatives to fossil fuels.

Table 1-1 Woody Biomass State Policies [Source: Becker and Lee (2008)]

State Abbreviation	Policy Type: Tax Incentive	Subsidies & Grants	Rules & Regulations	Education & Consultation	Financing & Contracting	Most Recent Enactment
AL	✓	✓	-	✓	-	2006
AK	✓	✓	-	-	✓	2008
AZ	✓	-	✓	-	✓	2008
AR	-	-	✓	✓	-	2007
CA	✓	✓	✓	✓	✓	2008
CO	✓	✓	✓	✓	✓	2008
CT	✓	✓	✓	✓	✓	2007
DE	-	✓	✓	-	-	2008
FL	✓	✓	✓	✓	-	2008
GA	✓	-		✓	-	2008
HI	✓	✓	✓	✓	✓	2008
ID	✓	✓	✓	✓	✓	2007
IL	✓	✓	✓	-	✓	2007
IN	-	-	✓	-	✓	2008
IA	✓	✓	✓	✓	✓	2008
KS	✓	-	-	✓	-	2008
KY	✓	-	✓	-	-	2008
LA	-	-	✓	✓	-	2008
ME	✓	✓	✓	-	-	2008
MD	✓	-	✓	-	-	2004
MA	✓	✓	✓	✓	✓	2007
MI	✓	✓	✓	✓	-	2008
MN	✓	✓	✓	-	✓	2007
MS	-	-	✓	-	✓	2006
MO	✓	-	✓	✓	✓	2009
MT	✓	✓	-	-	-	2007
NE	-	-	✓	-	✓	2007
NV	✓	-	✓	✓	✓	2007
NH	✓	✓	✓	✓	-	2008
NJ	-	-	✓	-	✓	2008
NM	✓	-	✓	✓	-	2007
NY	✓	✓	✓	✓	-	2008
NC	✓	✓	✓	✓	✓	2008
ND	✓	✓	✓	✓	-	2008
OH	✓	✓	✓	✓	-	2008
OK	-	-	✓	✓	✓	2007
OR	✓	✓	✓	✓	✓	2007
PA	-	✓	✓	✓	-	2008
RI	✓	-	✓	✓	✓	2005
SC	✓	✓	-	✓	✓	2007
SD	✓	✓	✓	✓	-	2008
TN	✓	-	-	✓	✓	2006
TX	-	-	✓	✓	-	2007
UT	✓	-	✓	✓	-	2008
VT	✓	✓	✓	✓	✓	2005
VA	-	-	✓	-	-	2007
WA	✓	✓	✓	-	✓	2008
WV	-	-	✓	✓	-	2006
WI	-	✓	✓	✓	-	2008
WY	✓	-	✓	-	-	2003

State Abbreviation	Policy Type: Tax Incentive	Subsidies & Grants	Rules & Regulations	Education & Consultation	Financing & Contracting	Most Recent Enactment

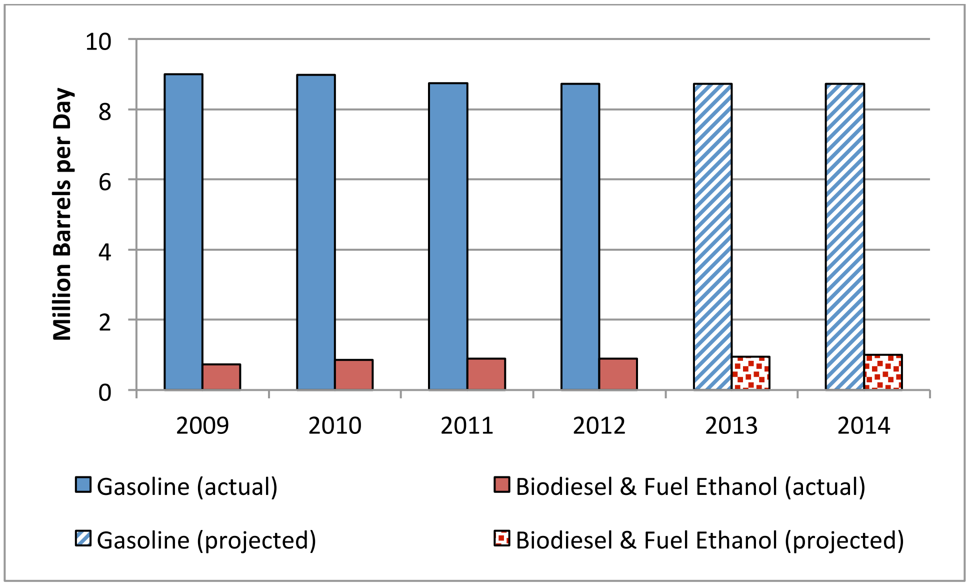


Figure 1-2 Fuel Consumption [Source: EIA:STEO Jan, '13]

Traditionally, higher production costs for biofuels have prevented their economic competitiveness with fossil fuels (Hill et al., 2006). The scale of operations utilized to produce the finished goods largely impacts these high costs, which result in higher consumer prices. Economies of scale would most likely significantly reduce the costs experienced by biofuel producers and make their products significantly less expensive for consumers (Ryan et al., 2006). Modeling has suggested that certain aspects of the current national renewable fuels standard (RFS2) may make it economically reasonable for existing biofuel producers to invest in expanding capacity in order to benefit from the growing consumer base and may increase the number of new market entrants (Kesan et al., 2012) thereby making economies of scale possible in the biofuels industry.

Besides poor economies of scale, a shift from reliance on fossil resources to agriculturally based feedstocks exposes previously unconsidered complications in the fuel supply chain. Factors such as seasonal variability in feedstock availability, variable feedstock moisture content, poor storability of perishable feedstocks, and complex product allocation issues when considering multiple conversion technologies can have significantly negative impacts on biorefinery operational ability (Gold and Seuring, 2011; Tay et al., 2011; van Dyken et al., 2010; Zhu et al., 2011).

1.2 Research Objectives and Questions

With the need for expanded supplies of biofuels established and several obstacles identified, work must be carried out to address these challenges. The objective of this research is to analyze the long-term economic performance of biorefinery supply chain operations in such a way as to capture the dynamic influences of uncertainty inherent to the system. Standard methods for solving location-allocation supply chain problems such as Mixed Integer Linear Programming (MILP) adequately capture the state of a supply chain for given static conditions defined by deterministic parameter values. In the case of biorefinery supply chain design utilizing only this type of model yields an optimal collection of feedstock supply locations, biorefinery siting, and points of sale for finished products. However, relying on deterministic inputs for variables such as product demand and supply availability greatly reduces the ability of the model to represent the true state of supply chain optimality. In this way, many uncertainties associated with biorefinery feedstock supply and product demand are overlooked.

Pitt (2013) reported on the recent record-setting payouts from agriculture insurers. Due to consecutive years of drought and flooding, US farmers received crop insurance payments of around $16 billion. This massive payout represents the insured value of lost crops. Not only does this represent a heavy financial burden for farmers and taxpayers; from the perspective of a biorefinery, the lost crops potentially represent a lull in feedstock supply availability. Clearly, as local supply diminishes, biorefinery decision makers could compensate for this lack of supply by sourcing from other suppliers. This action could maintain production, however, possible deviation from the optimal supply chain would have some negative impact on supply chain economic performance. Similarly, fluctuations in product demand could have similar impacts. Taking this type of variability into consideration by defining supply and demand variables using probability distributions over a longer time frame is paramount in establishing robust supply chains.

Analyses such as long-term supply chain profitability, deviation from the MILP defined supply chain, and policy application scenarios can be applied to more adequately discuss the supply chain including sources of local raw materials for the production of transportation fuels, chemicals, and electricity.

Overall, this work will address the following questions:

1. Is an optimized biorefinery supply chain always viable in a given region?
2. How is the profitability of a biorefinery supply chain impacted by variability in feedstock supply availability and product demand?
3. In what ways could the modeled supply chain be improved for long term positive economic performance?
4. How can policy decisions impact the viability of regional biorefinery supply chains?

The remainder of this thesis is divided into several more chapters. Chapter 2 includes a thorough literature review exploring existing biomass supply chain modeling as well as relevant supporting information. Chapter 3 describes the development of a new multidisciplinary framework for integrated biorefinery supply chain design. Chapter 4 describes the methodology employed to develop a biomass supply chain simulation model in the context of a larger modeling framework intended to provide decision support for biorefinery supply chain stakeholders. Chapter 5 is used to explain the illustrative case study employed to demonstrate the simulation methodology. In Chapter 6 analyses of the results from simulation are shown and, in Chapter 7, general observations of the results are discussed, conclusions are drawn, and future opportunities for expanding this work are discussed.

2 LITERATURE REVIEW

In order to assess the current state of the art related to biomass supply chain modeling and multidisciplinary approaches for tackling problems of this type, a survey of recent literature has been conducted. This section is divided as follows. First, in Section 2.1, rationale behind the need for supply chain modeling in the context of biofuel production is discussed. Second, in Section 2.2, the important topic of modeling uncertainty, particularly in the supply chain context, is covered. Next, Section 2.3 describes analytical methods and examples of biomass supply chain modeling. Section 2.4 identifies selected simulation-based methods for modeling. Finally, in Section 2.5, the work toward a multidisciplinary approach to address the issues related to biomass fed fuel and chemical production is highlighted by existing literature.

2.1 The Need for Supply Chain Modeling for Biofuel Production Planning

As highlighted in Section 1.1 (Background Information), numerous legislative drivers have biofuel poised to expand in the United States. The economic impact of the RFS2, for example, is expected to unfold similarly to that observed as conventional fuel ethanol infrastructure was being created. With lignocellulosic biofuel mandated as well, however, the implications for agriculture, land use, and economy in general are potentially larger (Beckman et al, 2011). It has been suggested that the effect of policies that increase the competitiveness of biomass based fuels is crucial to their development (Soloman, et al 2007). This type of government aid is meant to limit new industry entrant exposure to risk as they enter a market segment without a large-scale industrial base (Gutterson and Zhang, 2009). Besides this mandated impetus, some scholars believe that biofuels can become cost competitive with fossil based counterparts on their own in the near future. Expected increases in agricultural yield, farming advances such as no-till methods, a large existing supply of potential biofuel feedstocks and other biotechnology advancements could greatly increase the feasibility of profitable biomass to biofuel supply chains (Hellenhaus, 2006). Bartle and Abadi (2010) further suggest that excess potential agricultural land could result from these factors in conjunction with declining population growth rates; they indicate that the utilization of this newly available land for the purpose of energy or biofuel production could help to accelerate the economies of scale necessary for widely profitable biorefinery supply chains.

Energy balance studies have confirmed the potential for profitable design of biomass supply chains. Hill et al. (2006) make the point that low input crops grown on marginal crop lands have markedly better economies than the traditional biofuels sourced from food crops. Wu et al (2007) found similar results when examining woody biomass as a feedstock in western Australia. They emphasize a need to focus on harvest and transportation optimization to ensure the viability of the potential nascent industry. Wellisch et al (2010) suggest that biorefinery supply chain systems have great potential for sustainable innovation. Direct employment in refinery jobs, indirect industry development to support the biorefining sector, and local utilization of agriculturally based energy feedstocks can together be powerful drivers of rural development provided that deliberate planning and assessment methodologies are followed. Iakovou et al (2010) emphasize the importance of utilizing waste biomass as feedstock in order to maximize societal and environmental benefits gained from biorefining. Ryan et al (2006) posits the increased energy security and rural development possible from the development of biofuel industries. It is impossible to discuss the implementation of biofuel supply chain systems without mentioning the food-versus-fuel controversy. Huang et al (2012), point out the potential tradeoffs related to the alleviation of poverty with industrial expansion of biofuel production and the indirect impacts of feedstock and non-feedstock agricultural product commodity price rises. These potential negative impacts must be considered. Cruz Jr., et al (2009) proposed a discrete-time input-output model based framework to examine the dynamic behavior of biorefineries and their supply chains. In modeling, biorefinery production level is adjusted to compensate for surplus or deficit feedstock levels to regulate these dynamics. The research found that biorefineries may experience undesirable sustained or slowly decaying oscillatory behavior in production levels. They conclude that policy based or market based interventions could help quicken the stabilization of the new industry.

In addition to these necessary compromises and tradeoffs, hurdles do exist to the widespread establishment of biorefinery supply chains. For Europe, McCormick and Kåberger (2007) described these as economic conditions, know-how and institutional capacity, and supply chain coordination. Economic conditions such as relatively low fossil fuel prices make biobased transportation fuels non-competitive with their fossil based counter parts; this is largely linked with their third point. Low biomass bulk density as well as relatively low calorific values associated with biomass result in high feedstock requirements for biorefineries and, thus, high transportation costs to deliver it (Richard, 2010). Poor storability of biodegradable feedstocks also contributes to complications and supply chain uncertainties (Gold and Seuring, 2011). The implementation of widespread production of biofuels is prohibited, to some extent, by the high capital investment required to update infrastructure. When discussing the potential for biobased bulk chemical production in the United Kingdom, the BREW project report (Patel et al 2006) concluded that the challenge in developing the industry was primarily an economic one. The researchers pointed out that technological improvements and advances are crucial to bringing down the cost as well. Charlton et al (2009), while assessing the feasibility of biorefining in Wales, insisted that biorefineries ensure feedstocks are produced using only marginal land and foster the creation of locally sourced biomass supply chains with the ability to eventually integrate into a larger economic system. They point to the local transportation system's ability to handle increased demand for its use as a limiting factor to biorefinery development and general alternative fuel production adoption. Despite the fact that ample supply for sustainable supply of approximately 1 billion tons of biomass production each year for energy needs has been hypothesized and validated (Perlack et al, 2005 and Downing et al, 2011, respectively), similar challenges face alternative fuel producers in the United States.

With all these considerations, modeling is helpful for determining influencing variables, supply chain impact, and supply chain viability for a nascent biorefining industry. Appelqvist et al (2004) provided a literature review covering the topics of product and supply chain design. This analysis categorized the modeling in surveyed research as 'reengineering,' 'breakthrough,' 'continuous improvement,' and 'design for logistics' according to the state of the supply chain and product being considered. Table 2-1 illustrates this taxonomy.

Table 2-1 Research Classification Adapted from Appelqvist et al (2004)

Supply Chain	New	Reengineering	Breakthrough
	Existing	Continuous Improvement	Design for Logistics
		Existing	New
		Product	

For the case of biorefining, research can fall into any of these categories. First generation corn ethanol supply chain design via optimization, for instance, could be considered Reengineering because the existing product is being examined in light of a new supply chain. The result of optimization is the supply chain layout itself. Along these same lines, lignocellulosic biofuels and related technologies, a much newer innovation, could be considered a New Product. Therefore, the design of a new supply chain via modeling in this context would constitute research in the upper right quadrant of the table. Through literature review in the broader supply chain context, Appelqvist (2004) notes that simulation and optimization methods are often chosen for these models; the researcher further highlights the fact that the vast majority of literature surveyed fell in the domain of either reengineering or continuous improvement. Very little research was reported in the 'Breakthrough' domain, none in relation to lignocellulosic biomass supply chain design. Although the remainder of this literature review will show that in the years since the publication of Appelqvist (2004) significant levels of research have expanded the literature in these domains, work still remains to be done.

2.2 Uncertainty in Biomass Supply Chain Modeling

Awudu and Zhang (2012) reviewed literature relating to uncertainties and sustainability aspects of biofuel supply chain management. The pair classified sources of supply chain uncertainty in this context. Table 2-2 summarizes their findings.

Table 2-2 Sources of Uncertainty in the SC [Source: Awudu and Zhang (2012)]

Source of Uncertainty	Details	Year	Researcher(s)
Supply	Quantity of Feedstock	2000	Nagel
		2007	Caeser et al.
		2008	Dauzenberg and Hanf
	Availability of Arable Land	2003	Berndes et al.
		2009	Ravindranath et al.
Transportation	Delivery	2009	Schmidt et al.
	Intermodal	2009	Ekşioğlu et al.
Production and Operations	Supply of Raw Materials	2009	Cruz Jr. et al.
	Inventory Balance	2010	Ochoa et al.
Demand and Price	Market Volatility	2007	Meyer
		2010	Markandya and Pemberton
	Raw Material Cost	2009	Ravindranath et al.
	Market Size	2010	Cadre and Orset
Other	Carbon/Nitrogen Emissions	2006	Mortimer and Elsayed
		2008	Hammond et al.
	Tax Policy	2005	Rozakis and Sourie

As is clear from the table, researchers have noted various sources of uncertainty in biomass supply chains. Besides those noted by Awudu and Zhang in their literature review, many other sources of biomass supply chain uncertainty have been identified in the existing literature. Petrou and Pappis (2009) point out that the variety in modeling results obtained from various modeling of biomass supply chains is due to large variability in impacting factors such as local economies, climates, production methods, etc. Other researchers have explored problems such as the indirect land use change from biofuel production. This change naturally leads to many questions about the proper means to model these observations (Kim et al, 2009). Seasonal and regional variability of biomass supply (Zhu et al, 2011), varying moisture content of that supply (van Dyken et al, 2010), poor storability (Gold and Seuring, 2011), and complexity due to the variety of potential conversion technologies (Tay et al, 2011) are only a few additional sources of uncertainty in the system. Therefore, these highly stochastic systems must be analyzed to obtain a better understanding of this variability and the impact of means to deal with it. Various researchers have tackled this problem with varying results while others, for the moment, have avoided the question via assumption. Regardless, any robust biorefinery supply chain model should account for this uncertainty in some fashion.

2.3 Analytical Biomass Supply Chain Modeling

With increased legislative mandates for biobased energy and fuel production increasing over the last decade (Solomon et al, 2007), it should come as little surprise that so too has the interest in modeling the impacts and operations of biomass supply chains. As mentioned previously, unique hurdles and challenges related to the perishability of the feedstock, seasonal variability, transportation issues, etc. must be dealt with when considering the supply chain design. This variability, in turn, adds to the complications of practitioners as they attempt to provide biorefinery supply chain stakeholders with decision support.

Many articles in the literature focus on analytically modeling supply chain activities and design. Analytical models can include mathematical modeling formulations of various supply chain problems. Linear and nonlinear programming is a particularly prevalent method seen in the literature. Biorefinery supply chain performance at various degrees of resolution has been optimized via mixed integer linear programming on numerous occasions. Wu et al (2011) modeled economic performance of woody biomass use as a potential biorefinery feedstock in West Virginia. Giarola et al (2011) examined the supply chain implications of converting from first to second generation biorefinery technology with model based multiple objective mixed integer linear programming. With objective functions maximizing Net Present Value and minimizing GHG impact over twenty years, the results highlight important tradeoffs necessary between economic and environmental objectives. Gomes et al (2012) employed mixed integer programming to optimize chipping, storage, and delivery of wood biomass for fuel production. Many other examples of this type of supply chain optimization exist: several recent examples, among many others, are listed in Table 2-3 to show the persistent nature of the work in this area in recent years continuing to today.

Table 2-3 Recent Biomass Supply Chain Optimization Literature

Year	Researcher(s)
2007	Rentizelas et al
2009	Rentizelas et al
2010	van Dyken et al
2010	Lam et al
2011	An et al (references)
2011	Kim et al (a & b)
2012	Marvin et al
2012	Judd et al
2012	Faulkner
2013	Foo et al
2013	Kelloway et al
2013	Shabani and Sowlati

Zamboni et al (2009) presented a spatially explicit static mixed integer linear programming model that sought to capture the demand uncertainty via the use of various scenarios. Dal-Mas et al (2010) expanded on Zamboni's model to include uncertainties in production cost and selling price. These examples do provide insight into the impacts of uncertainty; however, they fail to capture probabilistic uncertainty present in the system as well as potential dynamic effects. Other research also attempts to capture uncertainty in a similar way, via scenario setting. For instance Zhu et al (2011) included buffer stock in a mixed integer linear programming model to deal with uncertainty; similar shortcomings exist for these examples as well.

To begin to address this issue, Dal-Mas et al (2011) later proposed a dynamic mixed integer linear programming expansion of this problem considering market uncertainties. The problem is formulated as a stochastic problem to account for the uncertainties related to biomass availability as well as market demand for the finished good.

Stochastic modeling has also been utilized to probabilistically address biorefinery supply chain risk. Baptista et al (2012) implemented stochastic modeling for this purpose in a closed loop supply chain. Bowling et al (2011) accounted for market uncertainties by considered nonlinear impacts of economies of scale on biorefinery supply chain design. The capital cost functions that made up the model were reformulated using disjunctive models; the results of the research yielded convex relationships that guarantee global optimality.

Awudu and Zhang (2012) have identified techniques used to model supply chains under uncertainty. While their work focuses on biorefinery supply chains, the researchers make the point that literature treatment of uncertainty specifically in the biorefinery supply chain context specifically is limited; they therefore generalized their literature review to include all supply chain uncertainty. The researchers have identified analytical and simulation based techniques. The analytical techniques of Awudu and Zhang (2012) can be seen in Table 2-4; the simulation-based techniques are shown in Table 2-5 in the next section. Analytical techniques included consist of various incarnations of mathematical modeling. The particular examples given highlight the use of stochastic variables to capture uncertainty.

Table 2-4 Analytical Biorefinery Supply Chain Modeling Under Uncertainty (Awudu and Zhang, 2012)

Method	Year	Researcher(s)
Stochastic Mixed Integer Linear Programming	2010	Dal-Mas et al.
Integer Stochastic Programming	2011	Kim et al.
Stochastic Mixed Integer Non-Linear Programming	2009	Sodhi and Tang
Stochastic Planning w/ Scenario Generation	2004	Lababidi et al
Markov Chain	2008	Al-Othman et al

2.4 Simulation Based Biomass Supply Chain Modeling

While mixed integer programming is by far the most common method of addressing biorefinery supply chain design, this method is often based on initial guesses and assumptions; there is not necessarily a guarantee of obtaining the global optimum solution (Johnson et al, 2012). A potential alternative to this type of analytical modeling is simulation based modeling. Akgul et al (2011) comments on optimization based methods for biofuel supply chain assessment under uncertainty. The work identifies mathematical programming as well as simulation-based methods as being relevant to this field. It is suggested that simulation based methods have the advantage of allowing the practitioner to identify detailed supply chain performance information even with significant levels of operational uncertainty in a system.

The IBSAL model, or Integrated Biomass Supply Analysis Logistics model, (Sokhansanj et al, 2006) considers weather influence, moisture content and dry matter loss from a supply chain perspective via simulation. The model is highly detailed, however, it provides no optimization or dynamic indication of supply chain performance. Slade et al (2009), while discussing the viability of lignocellulosic ethanol in Europe, make the point that supply chain performance in this context is dependent upon feedstock costs and the value obtained from ethanol. These two considerations are highly dependent on influencing factors that are inherently highly uncertain. Factors such as the price of oil or present and future policy incentives can fit this bill. Yun et al (2009) modeled optimal operation planning for biorefineries. The research described hedging options for biomass procurement that led to decreased profit variability. The work showed that with proper finance tools, firms could manage supply and demand uncertainty properly.

In 2004, Terzi and Cavalieri (2004) provided a survey of research focused on simulation modeling in the broader context of supply chains. These models were reportedly utilized for supply chain network design, strategic decision-making, inventory planning, distribution planning, and production planning. Kleijnen (2005) described techniques used for supply chain simulation modeling. At the most basic level, spreadsheet based simulation has been used for manufacturing resource planning and vendor managed inventory systems. Systems dynamics models elicit non-obvious emergent behavior from systems through nonlinear feedback interactions. Discrete event simulation is particularly well suited for supply chain operation modeling as it represents a quick and detailed view of individual supply chain events. Discrete event simulation modeling was utilized by Zhang et al (2012) to model woody biomass transportation for conversion into biofuel in Michigan. The model was exercised to show delivered feedstock costs, energy consumption, and greenhouse gas emissions from each supply chain event. Mobini et al (2011) used discrete event simulation modeling to estimate moisture content, carbon dioxide emissions, and cost of delivered biomass based on IBSAL modeling. Rangel et al (2010) quantified waiting times for harvesting sugar cane and unloading it in the. This model was not stochastic due to a general lack of probability distributions; however, many dependent variables resulted in a dynamic model, a possibility with discrete event simulation.

Table 2-5 Simulation-Based Biorefinery Supply Chain Modeling Under Uncertainty (Awudu and Zhang, 2012)

Method	Year	Researcher(s)
Discrete Event Simulation	2004	Jung et al
	2004	Kerbache and Smith
	2004	Higichi and Troutt
	2009	Miranda and Garribo
Monte Carlo Simulation	1994	Subrahmanyam et al
	2004	Jung et al
	2004	Hung et al
	2009	Mahnam et al
	2009	Miranda and Garribo

In several instances, Monte Carlo simulation has been used in recent years to quantify biomass supply chain uncertainty. Schade and Wisenthal (2011) identified policies for achieving EU biofuel objectives and compared them via analysis of expected opportunity losses via Monte Carlo simulation. They show that ranking of policy options via this method is valid and should replace the single variable sensitivity runs common in modeling. Similarly, Kim et al (2011) provided a global sensitivity analysis for an optimal design using Monte Carlo simulation. Rouch (2010) discussed the development of a sourcing model for forest biomass. Stochastic disturbances to supply were simulated via Monte Carlo method. Tay et al (2011) utilized fuzzy methods to optimize supply chain performance. In this context, fuzzy methods allow for simultaneous maximization of economic performance and minimization of environmental impact. Utilizing fuzzy methods allows the model to make “unexpected” adjustments to the objective function value, moving slightly away from global optimality to represent tradeoffs associated with these often-conflicting goals. Hytonen and Stuart (2010) employed Monte Carlo to assess technology risk for biorefineries using forest biomass as a feedstock. The model allowed for identification of the least-risk option. Yu and Tao (2008) developed an energy-flow based LCA of gasoline-ethanol blends from various biomass sources in regions of China including four life cycle stages for fuel products and three life cycle stages for vehicles. The model incorporated Monte Carlo simulation to account for model uncertainty.

2.5 Multidisciplinary Approach for Sustainable Biorefinery Supply Chain Design

An et al (2011) conducted a thorough comparative literature review of existing biomass and petroleum based fuel supply chain related literature. Broadly, the survey supports the assertion that research in this domain can be classified on the basis of decision timeframe considered and the point in supply chain where the modeling is set. The review goes on to classify several literature examples according to these considerations. It is evident from the reviewed literature that research integrating strategic, tactical and operational levels of decision making was lacking. This is illustrated by the taxonomy developed by An et al (2011). The researchers applied the taxonomy to specifically biofuel supply chain literature; these results are presented in Table 2-6. It is clear that upstream models at the operational level dominate the examined body of work.

Table 2-6 Literature Taxonomy [Source: An et al (2011)]

SCM Planning Level	Layer in Supply Chain	Year	Researcher(s)
Operational	Upstream	1984	Jenkins et al.
		1992	Mantovani and Gibson
		1996	Gallis
		1997	De Mol et al.
		1999	Gemtos and Tsiricoglou
		1999	Murray
		2002	Higgins
		2003	Tatsiopoulos and Tolis
		2004	Higgins and Postma
		2005	Goycoolea et al.
		2005	Gunn and Richards
		2005	Hamelinck et al.
		2005	Martins et al.
		2006	Sokhansanj et al.
		2007	Gronalt and Rauch Peter
		2007	Kumar and Sokhansanj
		2007	Petrou and Mihiotis
		2008	Constantino et al.
		2008	Lejars et al.
		2008	Ravula et al.
	Up/Midstream	1999	Higgins [23]
Integrated	Upstream	1997	Cundiff et al.
		2002	Gigler et al.
		2004	Gunnarsson et al.
		2005	Troncosoa and Garrido
		2007	Dunnett et al.
		2010	Zhu et al.
	All	2009	Ekşioğlu et al.
		2010	Ekşioğlu et al.
		2010	Huang et al.

A more holistic view of the supply chain is necessary for assessing the true environmental, economic, and societal impact of a biorefinery. Ekşioğlu et al. (2009) made the point that long and medium term biorefinery supply chain decisions and short-term logistics decisions should not be made in isolation; communication is key. They further noted that since these decisions are directly impacted by transportation costs and biomass availability, benefits may be seen from a system of 2 or 3 small biorefineries as opposed to 1 centralized location. Similarly, in 2009, Cundiff et al suggested that, due to the distributed nature of biomass, small, localized biorefineries could be more economical, environmentally friendly, and socially responsible than large centralized facilities. This viewpoint, the researcher points out, means that the interactions between feedstock production, logistics, and processing would be key to developing efficient supply chains. These considerations, it was noted, must be addressed concurrently. Along these lines, Kokossis and Yang (2010) took a systems view of biorefineries. This method of thinking requires attention to interconnections among existing subsystems. By doing this, the researchers claimed to maximize process efficiencies across the system through better design and optimizing activities such as process integration.

In past supply chain research, application of various tools with information sharing has proven to enhance the validity and impact of the overall model. A good example of this is the integration of GIS with modeling techniques such as LP to examine region specific biorefineries. For example, Tittmann et al (2010) combined GIS information with mixed integer programming to determine the optimal supply chain for a biorefinery located in California. Information made available to the model through integration of GIS made the model much more realistic. Similarly, Zhang et al (2011) and Schardinger et al (2012) incorporated geographic modeling results into linear optimization. Ayoub and Yuji (2012) take regional biomass availability into consideration during genetic algorithm modeling to optimize biorefinery supply chains. Given regional biomass resource availability, alternate production paths are chosen for some products. Miyazaki et al (2012) link linear programming with chemical process optimization. The amount of product optimally produced is used as an input to the linear program and capital cost is calculated.

Benefits can be gained from combining simulation and optimization for biochemical processing. Furlan et al (2012), Sukumara et al (2012), and Caballero et al (2012) combined process simulation and optimization. In this way, the optimal chemical process is selected for a given feedstock or product. Elia et al (2011) conducted process simulations for biomass, natural gas, and coal combinations. The feedstock requirements, production of finished goods, Hydrogen input requirements to drive the reverse water gas shift reaction, electricity requirements for operations, and plant unit sizing obtained from this process modeling were used as inputs in a mixed integer linear programming supply chain model. Elia followed this work (Elia et al. 2012) with the application of this system for the entire United States. The study found that while a combination of biomass and fossil resources such as coal or natural gas could replace petroleum-based fuels in the United States, certain tradeoffs among economic and environmental factors couldn't be overlooked. Nevertheless, profitable supply chains and significant potential for relatively positive environmental impact were demonstrated. This combination of biorefinery supply chain optimization and chemical process simulation yielded a very powerful tool for assessing the feasibility of multifeedstock integrated biorefineries in the United States.

Del Mol et al (1997) created a framework for simulation and optimization for biomass supply chains. An optimization model determined the network structure and optimal biomass types. This aspect of the model provided a strategic level view of the supply chain. Simulation, on the other hand, revealed more detailed results about operations and logistics, providing a tactical viewpoint. Ayoub et al (2007) described the general BioEnergy Decision System (gBEDS). This theoretical system would combine information databases with genetic algorithm modeling to find optimal conversion paths and simulation to check economic and technical feasibility. The model was demonstrated for 1 biomass feedstock on a national scale in Japan. The lack of regional information and the limit on feedstock options, however, means that supply chains modeled may not be globally optimal. Ingalls et al (2008) discusses the combination of optimization and simulation. Given the optimal solution, simulation allows for the researcher to explore how the optimal solution performs under dynamic conditions. In the supply chain context, such a combination is shown to reveal revenues and costs, advantages gained from tax policy changes, and how supply chain dynamics effect supply chain performance. Zheng et al (2008) describes simulation optimization as part of an overview of simulation techniques seen in supply chain research. Here, a stochastic approximation is used with discrete event dynamic system with continuous inputs. You et al (2012) combined multiobjective mixed integer linear programming, economic input-output modeling, and life cycle analysis (LCA) to determine optimal solutions. In this way, social impact and environmental impact have been taken into account along with economic considerations. Mardan and Klahr (2012) minimize the cost of operating an iron foundry by combining optimization and simulation modeling. The researchers found that running simulation alone does not guarantee optimality. The use of both optimization and simulation techniques allows the analyst to monitor the condition of the simulated result and ensure optimization.

As indicated by the reviewed body of literature, there is clearly a need for biorefinery supply chain modeling. Combining analytical and simulation based modeling techniques can leverage the benefits of both. Integration of process optimization and simulation with supply chain optimization and simulation, as the following chapters will discuss, allows for many benefits to be gained.

3 MULTIDISCIPLINARY APPROACH FOR BIOREFINERY SUPPLY CHAIN DESIGN

3.1 Overview

Much progress has been made in the field of biorefinery supply chain modeling. Parallel to this activity, biorefinery technology and chemical processes have been developed, simulated, and optimized. Although some exceptions do exist (Sammons, Jr et al, 2008 for example), the work in these two fields is often carried out independently with little multidisciplinary interaction. It has been demonstrated that biorefinery economic performance depends very heavily on biomass transportation expenses; therefore, it is not unreasonable to suggest that biomass supply chain performance relies heavily on factors such as biorefinery biomass input requirements and production rate of various finished goods. The complexity of the interdependence between supply chain design and chemical process modeling, then, is lost by considering biorefinery process optimization and biomass transportation cost minimization models in isolation.

With the goal of providing an overall framework to encompass these interdependent aspects of the design, a vision for multidisciplinary consideration of biorefinery supply chains has been developed. Figure 3-1 illustrates the necessary modeling components and information flows envisioned. Supply chain optimization and chemical process simulation models would work in conjunction to determine a base-case optimal supply chain, feedstock portfolio, and product slate for a selected region. Chemical process modeling should utilize regional biomass characteristics and multiple alternative potential conversion technologies to simulate chemical reactions. Furthermore, incorporating thermal pinch analysis, the chemical process should be optimized to minimize processing triple bottom line impacts. The supply chain optimization model should consider factors such as regional biomass availability, processing costs, transport costs, and other constraints in a mixed integer linear programming formulation of the resource location-allocation problem. These models together would provide the critical supply chain information mentioned; however, this pair utilizes deterministic inputs and falls short of capturing supply chain uncertainties. The true power of the multidisciplinary framework would be leveraged when outputs from these deterministic models provide input information for a long period supply chain simulation. Here, the optimal supply chain would be tested under dynamic conditions taking into account the stochastic nature of many of the supply chain activities. Utilizing the bidirectional information flows shown in Figure 3-1, a better supply chain design could be obtained. With the addition of quantitative, probabilistic risk analysis, to help manage the high levels of uncertainty inherent to the biorefinery supply chain, further improvements could be realized.

In subsequent sections of this chapter, more detailed discussions of each subcomponent of such a framework are provided. First, work toward chemical process simulation and optimization is addressed. Subsequently, efforts in supply chain optimization modeling are considered. Progress toward integrating probabilistic, Bayesian belief network based risk modeling is discussed. Finally, supply chain simulation is discussed. In general, its application would provide biorefinery supply chain stakeholders with a means to evaluate potential environmental, societal, and economic factors related to a regional biorefinery and its supplier and consumer base.

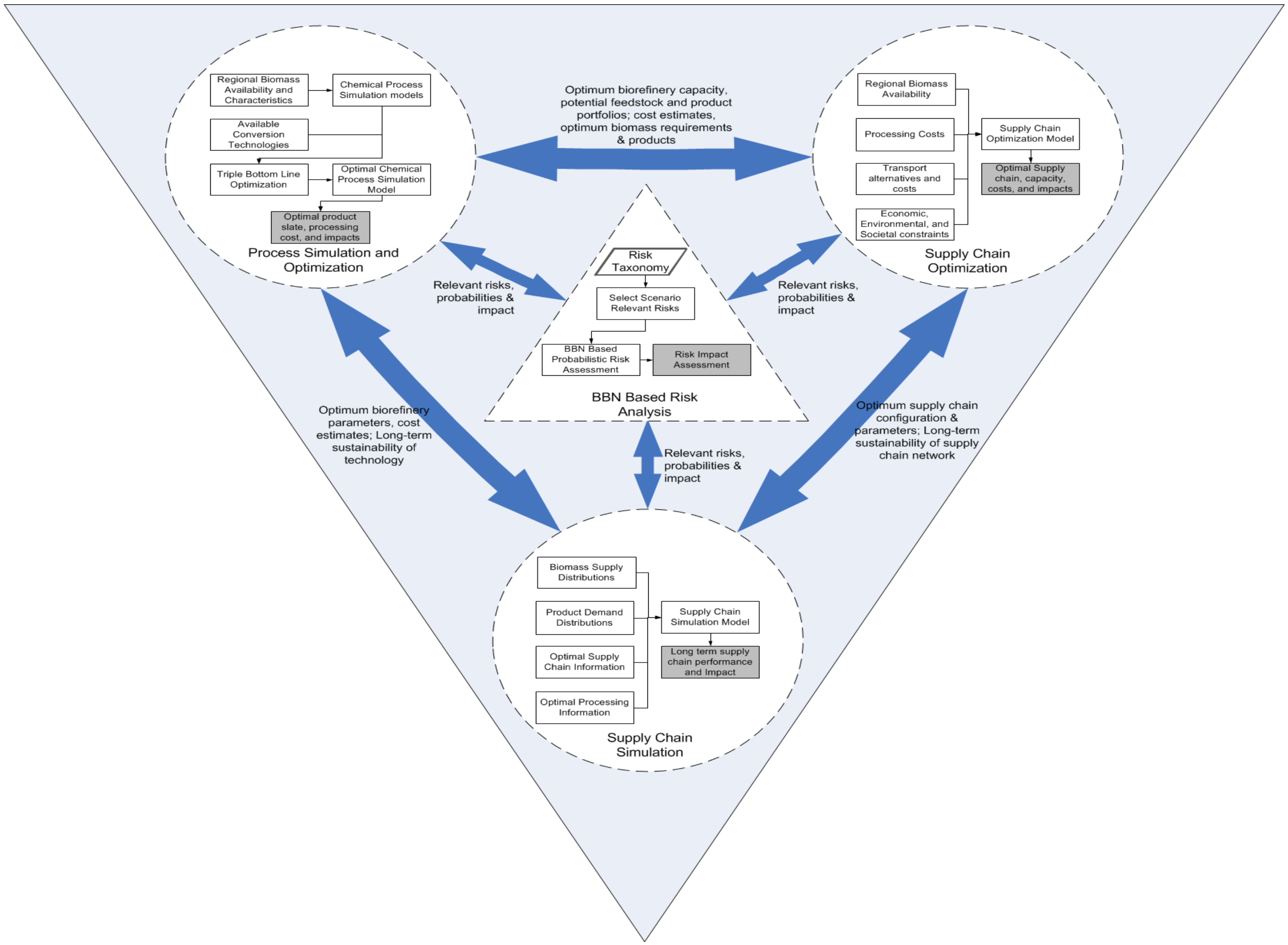


Figure 3-1 Multidisciplinary vision for a biorefinery design framework

3.2 Chemical Process Simulation and Optimization

With this vision established, Sukumara et al (2012) addressed the chemical process optimization of an integrated biorefinery. An integrated biorefinery combines multiple thermochemical and biochemical conversion technologies with the goal of diversifying feedstock requirements and product portfolios; this flexibility is thought to provide opportunities for more sustainable energy, fuel, and chemical production (Yun et al, 2009; Werpy et al, 2004; Naik et al, 2010). With feed flexibility, nontraditional sources for biofuel production can be considered. Dedicated energy crops (e.g. miscanthus or switchgrass), crop residues (e.g. wheat chaff or cornstover), wood residues from paper and timber mills, urban wood waste, animal manures, and municipal solid waste are all potential sources of biomass that should be considered for modeling and optimization in this context. Different feedstocks in combination with various conversion technologies can yield a variety of products for diverse markets as is illustrated in Figure 3-2. There, each arrow connecting feedstocks and products represents separate conversion pathway opportunities.

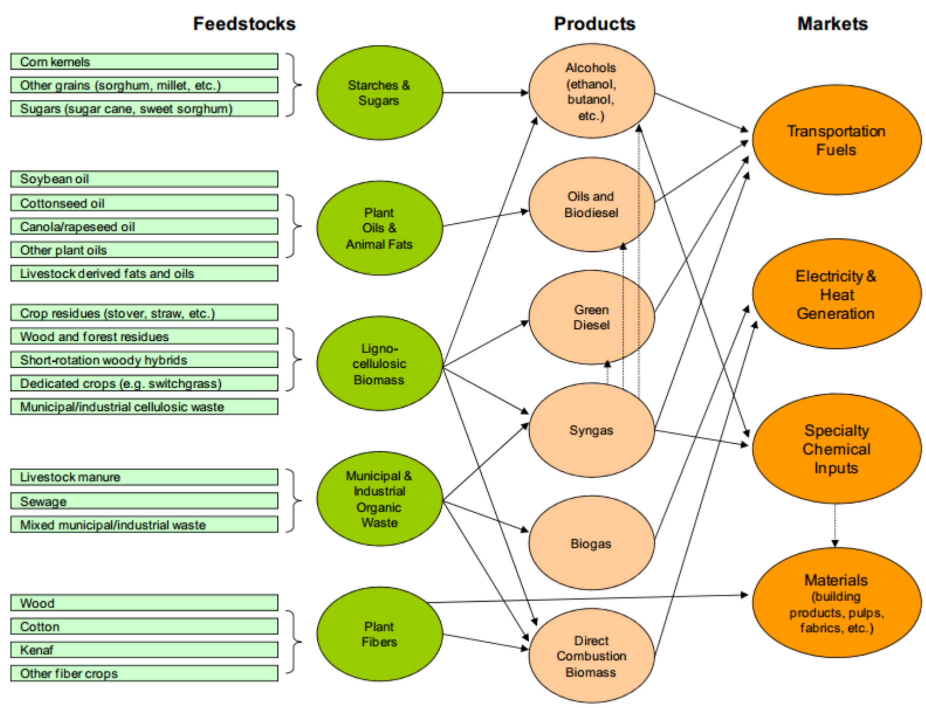


Figure 3-2 Potential conversion pathways [Source: Tripp et al, 2009]

Given an initial feedstock portfolio for a selected region, Sukumara et al (2012) determined an optimal product portfolio using Gasification, the Water-Gas Shift Reaction, and Fischer Tropsch Synthesis. The ASPEN® model for this design work can be seen in Figure 3-3. Optimization of the model including thermal pinch analysis minimized the biorefinery operating costs by minimizing electricity requirements, heating utilities and cooling utilities. This information along with the rate of production and the optimal product slate produced, as it will be shown, are important inputs for both supply chain optimization and biomass supply chain simulation models associated with the multidisciplinary vision for the development of biorefinery supply chain designs. Additional details of the chemical process optimization can be found in Sukumara et al (2012).

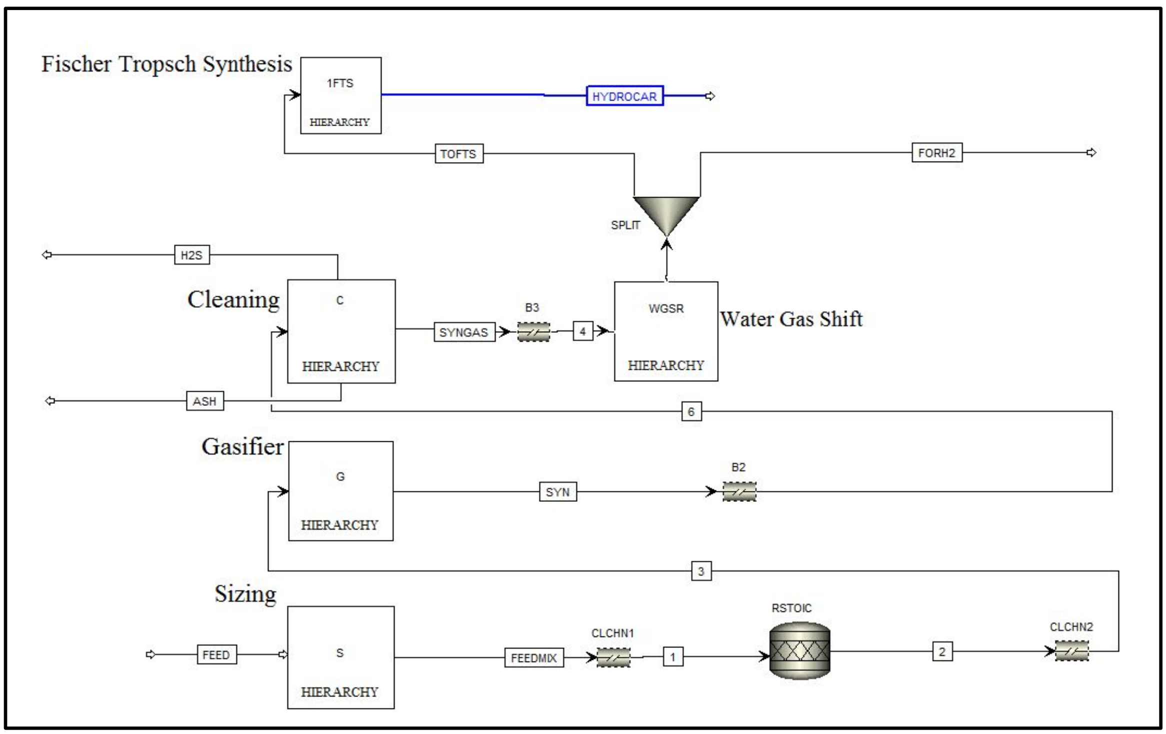


Figure 3-3 Feed flexible gasification process diagram [Source: Sukumara et al, 2012]

3.3 Supply Chain Identification and Optimization

Faulkner (2012) employed the results from the model shown in Figure 3-3 as part of the inputs using inter-model information sharing in line with the framework outlined in Figure 3-1. Additionally, literature data was used to model a second-generation fuel ethanol plant. Other modeling inputs included case region specific data related to biomass supply and product demand. Utilizing mixed integer linear programming, Faulkner (2012) maximized the profit from each biorefinerinery separately. The model identified the optimal supply chain configuration to source feedstock, locate the biorefinery, and distribute products to the market. For each technology (integrated biorefining with multiple feedstocks and ethanol from corn stover), a 'small,' a 'medium,' and a 'large' capacity biorefinery were described based on varying levels of feedstock consumption and the appropriate supply chain model was applied.

Optimal supply chain profitability over a year was determined by considering deterministic feedstock supply and product demand levels. Figure 3-4 shows that for the selected case study region (Jackson Purchase Region in Kentucky, to be explained in detail in Chapter 4), in general, the integrated biorefinery was not profitable regardless of capacity. The fact that certain months showed profit prompted the researcher to further analyze the integrated biorefinery supply chain for profitable scenarios; by allowing plant closure during the least profitable months, regional biomass supply chains could support profit with integrated biorefineries. It should be noted that the presented analysis includes the production and sale of a product, residual fuel oil (RFO), that was generated in the process simulation but not originally included in the modeled product slate (see Faulkner (2012) for additional details).

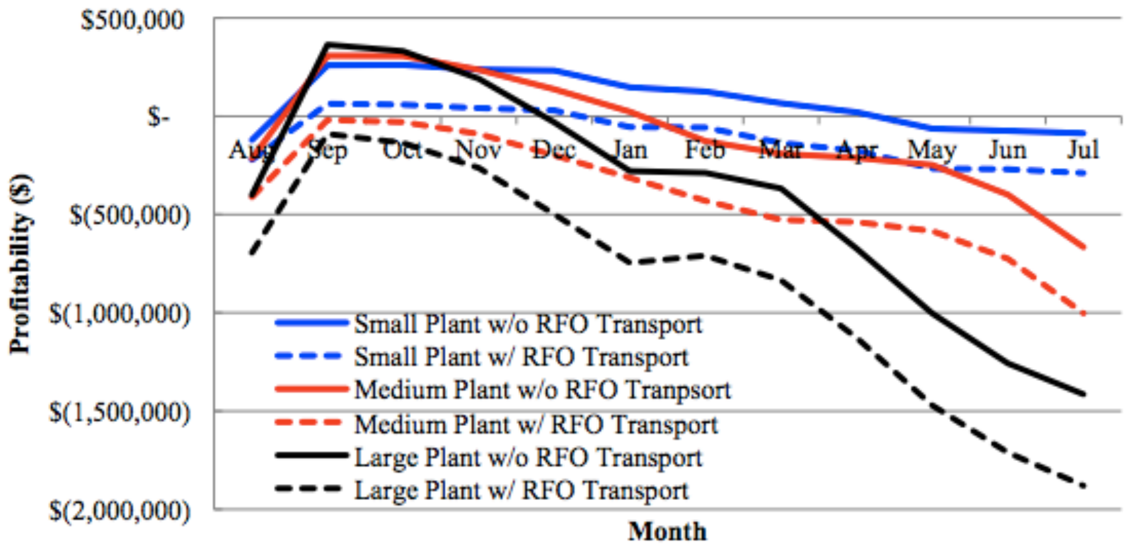


Figure 3-4 Monthly biorefinery supply chain profitability [Source: Faulkner, 2012]

As a result of modeling, the structure of an optimal supply chain configuration including biomass supply locations, a biorefinery site location, and optimal product distribution locations for the selected case study region were determined. Additionally, this case study demonstrates the first steps of collaborative work between chemical process design and supply chain optimization intended in Figure 3-1.

3.4 Bayesian Belief Network (BBN) Based Risk Modeling

With so much uncertainty related to, particularly, biorefinery feedstock supply availability, decision support systems developed should consider an assessment of the associated risks (McCormick and Kåberger, 2007). In this way, supply chain designs are more likely to limit supply chain costs and maximize return on investment.

Bayes Theorem, a fundamental description of the relationship between conditional events, reveals how newly observed information should be incorporated into event probabilities (Gut, 2005). The theorem has been applied to both the risk analysis and supply chain contexts in many instances (Nordgard and Sand, 2009; Weber et al, 2012;

Kelepouris et al, 2011; Badurdeen et al, 2013); its application in biorefinery supply chain risk assessment is more limited.

Amundson et al (2012) described the application of a Bayesian belief network based risk assessment methodology to a biomass supply chain. This model utilized a generic risk event taxonomy, describing risk events based on their scope of influence, be it at the individual farm, regional agricultural, or external level. Relevant risks were identified for a corn stover supply chain set in the Jackson Purchase Region of Kentucky. Subsequently, root cause analysis and the determination of the most influential risk drivers were carried out.

This demonstration case study presented by Amundson et al (2013) emphasizes the potential for this tool to provide information relevant to biomass supply availability. This insight could help inform the supply chain and process models pictured in Figure 3-1 via the information channels highlighted. Until now, only preliminary models have been developed; future work is required to expand the scope to include demand and processing risks and to identify the most useful applications of this model to biorefinery supply chain design.

3.5 Supply Chain Simulation – The Next Step

The work by Sukumara et al (2012), Faulkner (2012), and Amundson et al (2012) made great strides in moving towards a holistic supply chain design paradigm where information sharing could lead to a better supply chain design including the assessment of environmental and societal impacts.

The results for biorefinery stakeholders, however, can be improved by including the final piece of the framework pictured in Figure 3-1. Faulkner (2012) based product demand and feedstock supply on deterministic values that fail to capture the true complexity in which biorefinery supply chains are immersed. Encompassing stochasticity using a discrete event simulation model by including probability distributions to describe supply and demand and taking into account the time value of money over a longer time horizon provides a more complete picture of the biorefinery operational details. Such an analysis will also help assess the implications of drawing biomass feedstocks from farther locations than those identified as optimal by the MILP optimization. The following chapter describes the methodology taken to develop such a discrete event simulation model. Subsequently, analysis of the model reveals various insights that can be gained from incorporating this dynamic view of the supply chain into the design paradigm.

4 METHODOLOGY FOR THE DEVELOPMENT OF A SUPPLY CHAIN SIMULATION

The objective of this research is to develop a biomass supply chain simulation model capable evaluating the long-term operational performance of a supply chain network design. Additionally, this model fills a critical void currently present in the multidisciplinary framework visible in Figure 3-1. The simulation model provides a means to analyze biorefinery supply chain operations over a multi-year time horizon taking into consideration uncertainty related to feedstock supply and product demand. This scale of simulation allows for an assessment of the long-term viability of the network and economic benefits possible from biorefinery operation in a selected region.

Model development and analysis requires several steps. Scope definition where potential feedstock options and conversion technologies are considered is the first of these processes. Next, static supply chain and process optimization occurs. Here, optimal chemical processes and supply chain configurations are determined. Although input values are deterministic, this step provides invaluable inputs for the proposed simulation model. These crucial activities have been accomplished in previous work (Faulkner, 2012; Sukumara et al, 2012) as described in sections 2 and 3 of Chapter 3. The research presented in this thesis advances the achievements of these previously created models by including the explicit consideration of uncertainty in the system. Input data and simulation model development must occur by, among other activities, identifying data probability distributions for feedstock supply and product demand based on historic data. Finally, simulation modeling and system analysis takes place. The steps followed to achieve a biorefinery supply chain simulation model are highlighted with Figure 4-1. As the figure highlights with the differently colored borders, these activities can be subdivided into two major steps: Simulation Model and Input Data Development (Figure 4-1 A) and Simulation Modeling and System Analysis (Figure 4-1 B). Each subdivision is comprised of multiple activities; in the following sections of Chapter 4, each of these steps is described in detail.

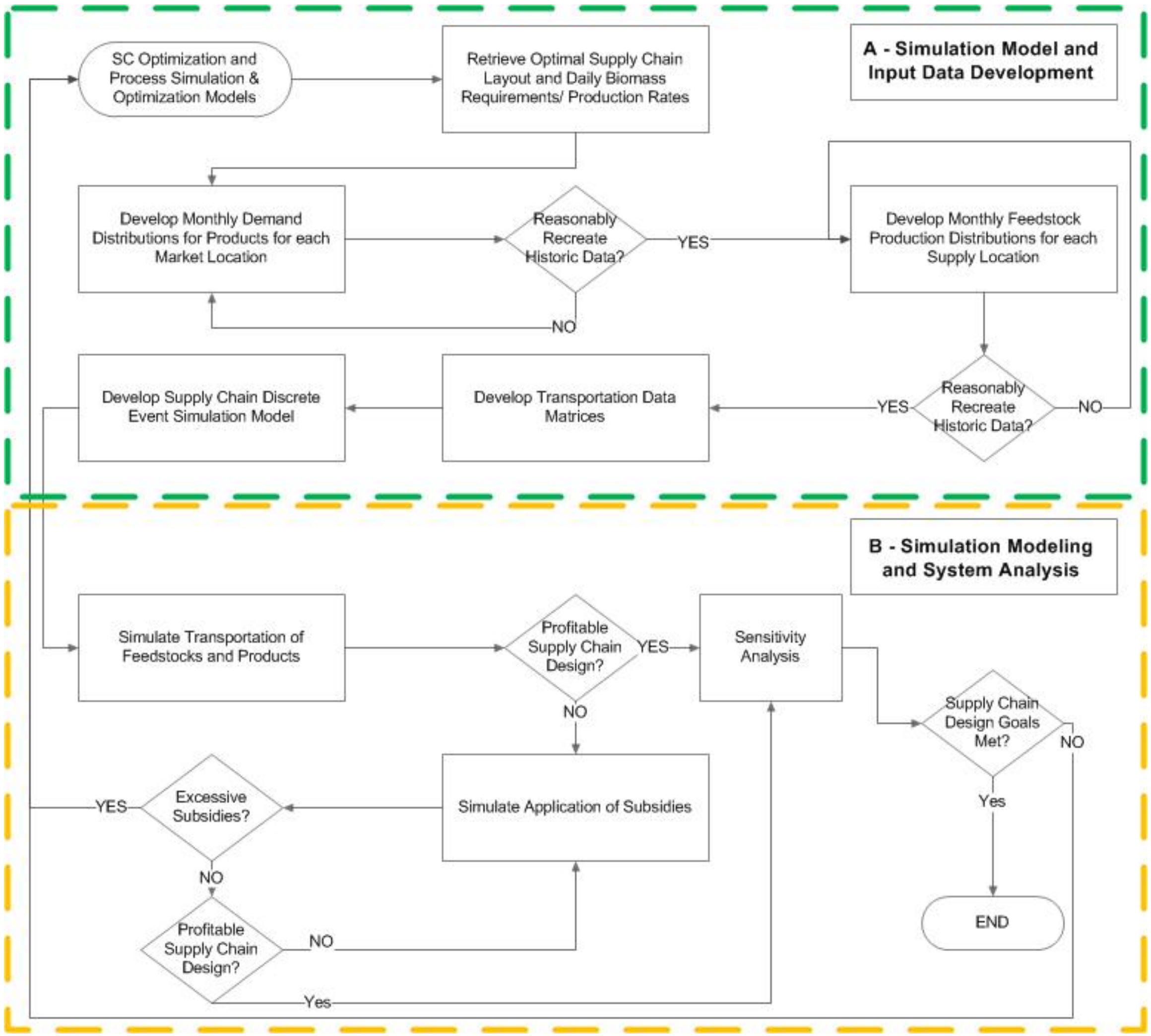


Figure 4-1 Methodology Outline

4.1 Input Data and Simulation Model Development

4.1.1 Input Data Development

As mentioned previously, supply chain and chemical process models have been used to determine optimal supply chain and product slate configurations based on deterministic input for values related to feedstock supply and product demand. Table 4-1 displays the variables and parameters used for supply chain optimization. An explicit goal of the simulation model is to incorporate uncertainty in the parameters. To do this, the data requirements of the model are different; probability distributions for reasonable input values are necessary. The values requiring such distributions are seen in Table 4-2 under the heading 'Random Variables' along with the other parameters and variables used in simulation. Compiled historic data should be fit to distribution functions for use in long-term discrete event simulation to describe product demand, supply availability, and operating costs. This section will describe in detail the development of these data distributions.

Table 4-1 Optimization Parameters and Variables [Source: Faulkner, 2012]

Deterministic Parameters		**Decision Variables**	
TM	*Truck mass*	**P**	*Product supply*
TM'	*Biomass truck capacity*	**X**	*Amount of biomass feedstock*
TM''	*Product truck capacity*	**Y**	*Amount of product*
ρ	*Density*	**Binary Variables**	
s	*Truck speed*	**P**	*Plant open*
d	*Distance*	**Subscripts**	
k	*Truck diesel cons'n conv'n*	**f**	*biomass feedstock*
T	*Number of trucks*	**p**	*product*
c	*Labor hrs. needed conversion*	**i**	*Biomass supply location*
c'	*Ethanol produced conversion*	**j**	*plant location*
B	*New supply of biomass*	**k**	*product location*
B'	*Aged biomass*	**m**	*month*
B''	*Total biomass availability*		
BN	*Biomass needed*	**ELEC**	*Biorefinery electricity cost*
E	*Biomass erosion factor*	**LC**	*Labor cost*
P'	*Product demand*	**LC'**	*Hourly labor cost*
L	*Product loss during transport*	**MC**	*Maintenance cost*
R	*Biomass land rent cost*	**MC'**	*Maintenance cost conversion*
BC	*Biomass purchasing cost*	**SC**	*Supervisor cost*
BC'	*Biomass transport cost*	**OVC**	*Overhead cost*
BC''	*Biomass transport diesel cost*	**PC**	*Product transport cost*
BC'''	*Biomass inventory cost*	**PC'**	*Prod. transport diesel cost*
BTC	*Biomass truck dist. dep't cost*	**PTC**	*Prod. truck dist. dep't cost*
BTC'	*Biomass truck time dep't cost*	**PTC'**	*Prod. truck time dep't cost*
OC	*Operating cost*	**DP**	*Diesel price*
COOL	*Biorefinery cooling cost*	**BP**	*Biomass purchase price*
HEAT	*Biorefinery heating cost*	**PP**	*Product selling price*

Table 4-2 Simulation Parameters and Variables

Deterministic Parameters		**Random Variables**	
D	*Distance*	***PD***	*Product Demand*
n	*Number of locations*	***S***	*Biomass Supply*
DBR	*Daily Biomass Requirement*	C_O	*Biorefinery Operating Cost*
DR	*Raw Material Decay Rate*	**Dependent Variables**	
MC	*Raw Material Cost per Ton*	**NPV**	*Net Present Value*
SW	*Raw Mat'l Shipment Weight*	**I**	*Income*
$TC_{BS}(t)$	*Bulk Solids Transport Cost*	C_T	*Cost of Transport*
$TC_L(t)$	*Bulk Liquid Transport Cost*	C_D	*Diesel Fuel Expense*
TS	*Truck Speed*	C_M	*Feedstock Expense*
CPM	*Cost per Truck Mile*	C_S	*Biorefinery Storage Cost*
TDR	*Truck Diesel Requirement*	**BS**	*Biorefinery Storage*
TW	*Truck Weight*	**BSA**	*Biomass Storage*
DP	*Diesel Price*	**PSA**	*Product Storage*
P	*Price of Product*	**PMA**	*Product Delivered*
r	*Daily interest rate*	***Binary Variables***	
DOC_A	*Daily Operating Cost-Aug*	***O***	*Plant Open*
$DOC_{S\text{-}J}$	*Daily Oper. Cost-Sep to Jul*	***SQ***	*Sufficient Quantity Available*
SC	*Storage Cost per Ton*	***OS***	*Member of Optimal SC*
SR	*Product Subsidy Rate/Gal*	**Subscripts**	
Array Variables		**i**	*Biomass Feedstock*
		j	*Product*
DA	*Distance Array*	**s**	*Biomass Supply Location*
DM	*Distance to Market Array*	**b**	*Biorefinery Location*
PMA	*Product at Market Array*	**d**	*demand location*
PSA	*Product Storage Array*	**m**	*month*
		t	*day*
		c	*Region of interest*

Assuming a profitable supply chain design has been identified via the supply chain and chemical process optimization models, development of a long-term simulation model commences. Several decisions for modeling purposes are informed based on the information obtained from scope definition and optimization modeling. Some of the major decisions necessary for consideration in the modeling phase include, among other influencing factors:

- Biomass conversion technology
- Product slate for the selected region
- Feedstock and product transportation method(s)
- Feedstock harvest method(s)
- Feedstock harvest schedule to consider and how to model this
- Incorporating surplus biomass treatment
- Consideration of biorefinery capital costs

Technologies available for biomass conversion to specific chemical and fuel products are varied. Options can include various combinations of thermal (torrefaction, pyrolysis, etc.), chemical (Fishcer-Tropsch synthesis, transesterification, etc.), and biochemical techniques (fermentation, anaerobic digestion, etc.). The specific combination of technologies for simulation input should be determined based on chemical process optimization given region specific biomass availability. Ideally, with multiple technological paths selected for comparison, optimal products are determined via process modeling and optimization to minimize electricity requirements, heat, and cooling utilities. Volumetric quantities of specific biomass required per unit time for optimal production is also gleaned from this activity.

Transportation methods should be regionally selected. In the United States, transportation of biomass and finished products via diesel fuel consuming trucks is generally a reasonable assumption. Readily available tools such as Google Maps™ can be leveraged to determine realistic distances between potential biorefinery locations and potential biomass source locations. In this way, realistic distances can be generated quickly based on the actual infrastructure available. Where relevant, simulation modeling can be altered to include alternative shipment modes such as barge or rail transportation. In many cases, it is feasible that such shipment methods could drastically reduce the transportation cost associated with supplying raw materials to a biorefinery. Figure 4-2 illustrates the cost structure associated with biomass and ethanol transportation in a case study from Illinois. Noticeably, for certain scenarios and supply chain designs, the utilization of larger volume transportation systems may yield significant cost savings. It is clear that the best mode of transport for a supply chain configuration is a function of the average required distance to travel, total volume of material to be transported, and the costs (fixed and variable) associated with transportation activities.

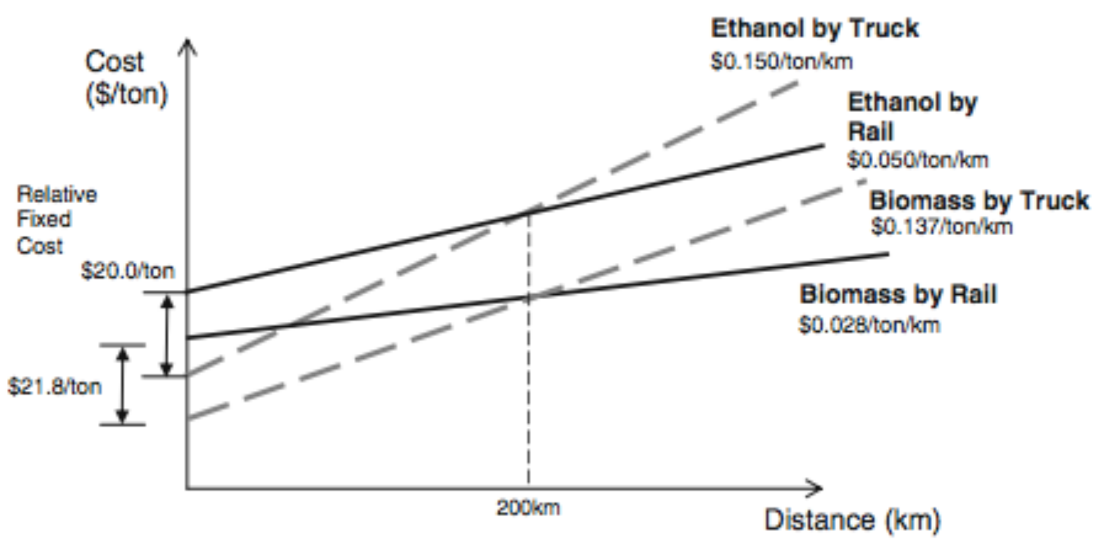


Figure 4-2 Cost structure for ethanol and biomass transportation (Kang et al, 2010)

Utilizing the potential biorefinery and biomass resource locations, a distance matrix consisting of travel distances between the biorefinery and each supply location should be developed. This matrix will be used as an essential input for the discrete event simulation. An example is shown in Table 4-1. In the table four possible biorefinery locations ten source locations are represented. Values in the interior of the matrix represent the distances between biorefinery locations and each supply location. These values were identified utilizing Google Maps™ in order to employ real and existing road infrastructure. A binary variable is utilized to indicate which of these biorefinery location options are being examined. The exact biorefinery location is another output from static mixed integer linear programming optimization mentioned earlier. Another binary variable is utilized to indicate the supply source locations that have been identified via the mixed integer linear programming process as optimal. In Table 4-3, the 5th, 6th, and 7th biomass source locations are indicated as optimal. The final column (with the heading "Sufficient Supply?") is a variable used to indicate when a supply location's resources have been depleted to a level where shipment cannot be completed. These variables are used in the simulation to track deviations from the designed optimal supply chain. Similar matrices can be developed to reflect product transportation distances.

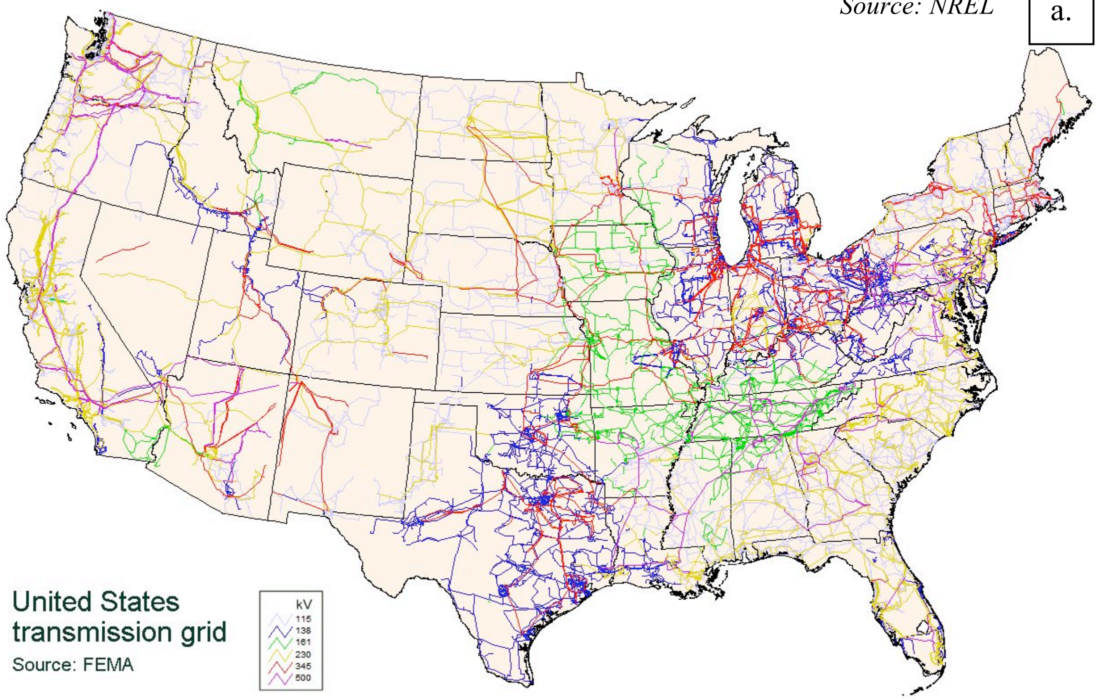
Table 4-3 Example distance matrix developed for use in simulation modeling

Optimal Supply Location			Biorefinery Location (b) 1	2	3	4
Number (s)	OS_s	SQ_{si}	OS_b 0	1	0	0
1	0	1	21	69.8	29.6	61.9
2	0	1	8.7	72.3	17.2	49.6
3	0	1	9.1	52.2	14.6	46.9
4	0	1	15.3	62.6	23.9	56.2
5	1	1	60.3	5.3	55.8	56.4
6	1	1	50.1	9.7	45.6	55.1
7	1	1	55.4	7.9	50.9	50.7
8	0	1	11	44.1	6.5	38.8
9	0	1	14.7	46.7	6.2	35.8
10	0	1	13.2	53.9	4.7	27.7

Various products generated through integrated biorefining may be treated differently. For instance, it is assumed that electricity and natural gas produced in a regional biorefinery could be delivered directly to existing infrastructure (pipeline for natural gas and the national electrical grid for electricity) and, therefore, transportation costs for these products are considered to be zero. For most states in the USA, this assumption is valid. In Figure 4-3 the US national transmission grid and natural gas pipeline infrastructure are juxtaposed; it is clear that most of the country and all population centers have access to these. In places where this is not the case, modifications could be made to the simulation model in order to take into consideration the usage of these products to offset operating costs for the facility, given some additional capital expenditure. Currently, it is assumed that all products produced are delivered to the market and sold; electricity utilized for the biorefining processes is assumed to be purchased from the grid and diesel consumed in transportation is assumed to be purchased at the market rate.

Source: NREL

a.



Source: EIA

b

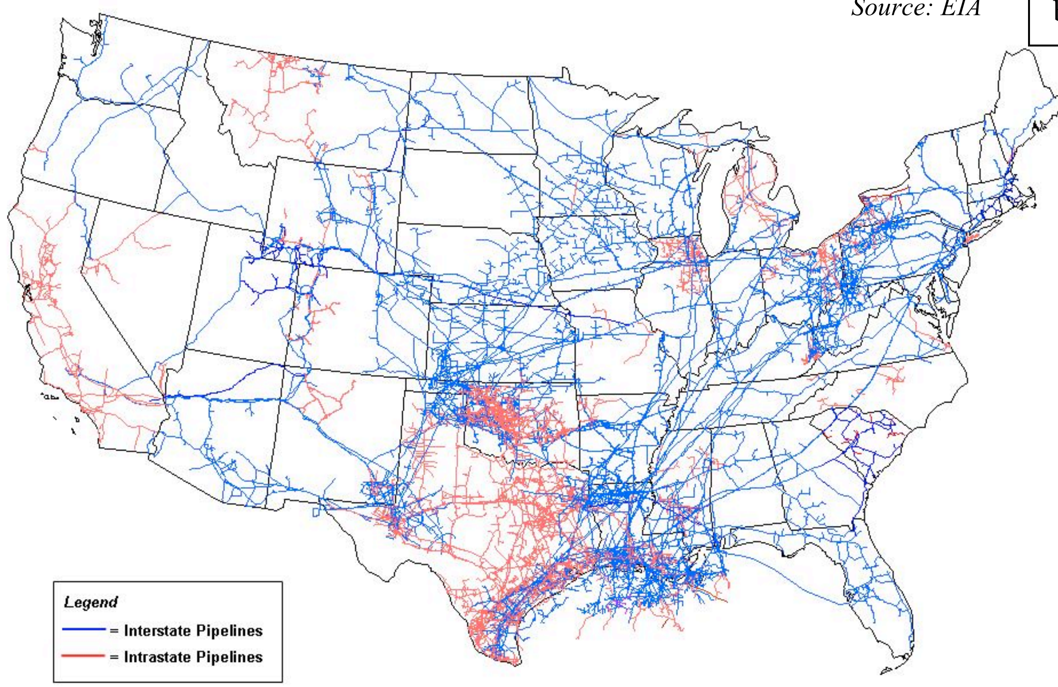


Figure 4-3 National (a) transmission grid and (b) gas pipeline infrastructure

Next, demand distributions for the selected optimal products should be determined. It is necessary to define a distribution for each region of consideration for each month of the year. Publically available historical data related to regionally specific consumption of fuels and electricity can be gathered from the Energy Information Administration via their website. Once collected, this data can be plotted for each region for each month. Likely, examination of the data will reveal groupings of similar demand behavior in specific similarly populated areas, for example. With these groups identified, combined data points for the can be fit to composite distribution functions for use in the discrete event simulation model using ARENA Input Analyzer. The expected value of the distributions as well as the variance expected can be plotted to show that historically reasonable demand values can be generated with the defined distributions.

Besides product demand, distributions of supply levels at feedstock sourcing locations must also be developed. These represent the amount of new biomass available each day for transport to the selected biorefinery location. Similar to the demand distributions, regional level data for each month can be conglomerated from sources such as the National Agricultural Statistics Service. Data for these regions can be aggregated from multiple years in order to determine a reasonable expected value and variance for the biomass supply.

For both supply and demand, the generation of specific distributions is presented with the case study in Chapter 4.

4.1.2 Simulation Model Development

In general, DES models represent reality as a sequence of events that each change the state of a system at an instant in time. In this research a discrete event simulation (DES) model is developed to simulate the activities observed in supply chain activities to deliver biomass feedstocks to the biorefinery and products from the biorefinery to demand locations.

The events included in the model developed are represented in the flow chart in Figure 4-4. In this section, the general approach taken to model these events is described. In chapter 5, these will be described more specifically in the context of the case study.

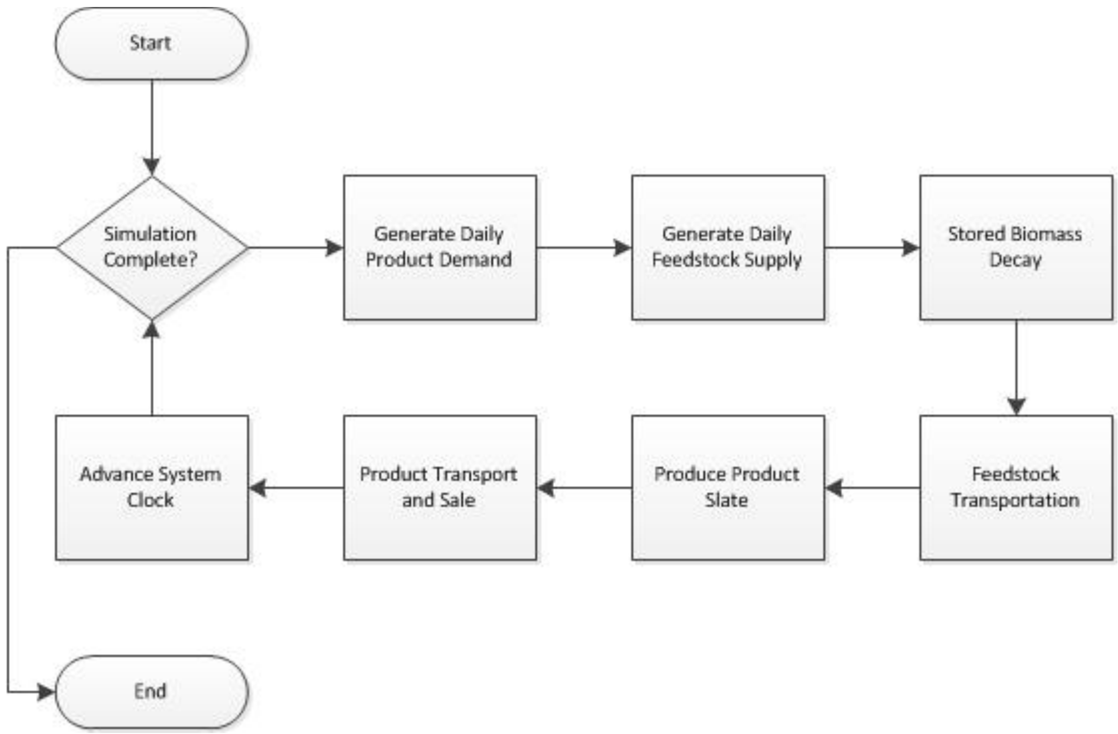


Figure 4-4 Sequence of Events Modeled

Traditionally in DES, entities in the system represent a customer, unit of production, etc. In the case of the biomass supply chain under consideration, this viewpoint is also valid; however, certain complications quickly emerge. Due to the long time scale of the simulation model as well as the desired resolution of data retrieved from the model, modeling each unit of biomass as entities resulted in large numbers of system entities, long runtimes, and, in some cases, an inability to divide the base unit. For instance, defining an entity of biomass feedstock as 1 ton of the biomass limits the ability to base shipments on truck volume, demand at the biorefinery, or to ship fractions of tons of biomass. To alleviate these problems, the DES model developed contains only one entity. This serves essentially as a place keeper for processes and advances the clock as discrete events are completed. All data parameters relevant to biomass supply, product demand, associated costs, processing, etc. are tracked utilizing user-defined variables in ARENA. Several variable values are currently assumed. Table 4-2 lists the variables that have been taken as deterministic for the purposes of modeling.

The power of the simulation model comes from the uncertainty captured by the use of random variables. Table 4-2 lists the random variables generated from input distributions included in the simulation; the development of these distributions was described in section 4.1.1. Additional dependent variables in the simulation rely on various combinations of random and deterministic variables and parameters. Therefore, these can be considered to be random variables. In particular, the variable BSA (the biomass storage array) is a vector variable that represents the total biomass supply. The sum of the values of the random variable S_{ic} (which represents feedstock (i) production in a particular region (c)) over all months (m) under consideration divided by the number of supply locations (s) for feedstock (i) in region (c), n_{sic} for each of the supply locations (s) in region c gives the value for entries in the vector BSA. This is expressed in equation 4-1 below.

$$BSA = < \left(\sum_1^m S_{1,c}\right)/n_{s1c}\,, \forall s,c; \left(\sum_1^m S_{2,c}\right)/n_{s2c}\,, \forall s,c; \dots; \left(\sum_1^m S_{i,c}\right)/n_{sic}\,, \forall s,i,c > \qquad (4\text{-}1)$$

Modeling of each discrete event is accomplished by utilizing combinations of basic and advanced process elements in ARENA simulation software. The modeling of events illustrated in Figure 4-4 is described here. Region level demand for each of the optimal products (j) is generated as a random value, D_{jcm}, from the distribution developed as described in Section 4.1.1. This value is determined for each product considering the specific month in the simulation timeline. The county level demand for each product (j) is then evenly divided among the selected market locations within the county, n_{djc}. Similarly, the daily biomass supply of feedstock (i) that becomes available at each supply location (s) is dependent on the random variable S_{icm}; these values are generated based on distributions specific to each month (m) and each region (c). The supply from individual locations is determined by evenly dividing the county-level value among the selected locations, n_{sic}. These individual supply and demand variables are stored as array variables (BSA and PSA, respectively).

The perishable nature of biomass feedstocks necessitates the consideration of decay due to microbial action of bacterial, fungi, etc. To accommodate this, biomass held in storage is allowed to decay based on a simple linear relationship shown in Equation 4-2 where DR, the raw material decay rate is a constant defined by literature and BSA' represents the updated variable BSA.

$$\boldsymbol{BSA' = BSA * (1 - DR) \quad \forall s, i} \tag{4-2}$$

Feedstock transportation is then modeled in ARENA utilizing search modules to find the shortest distance supply location for a given raw material (i) utilizing a search module and a distance array variable (DA) containing the information described and presented in Table 4-3. DA is defined specifically as Equation (Set) 4-3 where the subscripts p and q represent the rows and columns of the matrix DA, respectively. The parameter D_{sb} represents the distance from feedstock source (s) to the biorefinery location (b) in keeping with the notation shown in Table 4-3.

$$DA_{pq} = \begin{cases} \boldsymbol{OS_b = \begin{cases} 1, & if\ p = 1, q - 1 = b \in\ optimal\ supply\ chain \\ 0, & if\ p = 1, q - 1 \neq b \in\ optimal\ supply\ chain \end{cases}} \\[2ex] OS_s = \begin{cases} 1, & if\ p - 1 = s \in\ optimal\ supply\ chain\ , q = 1 \\ 0, & if\ p - 1 \neq s \in\ optimal\ supply\ chain, q = 1 \end{cases} \\[2ex] SQ_{si} = \begin{cases} 1, & if\ p = s + 1, q = max\ \{b\} + 2\ AND\ BSA_{si} \geq SW_i \\ 0, & if\ p = s + 1, q = max\ \{b\} + 2\ AND\ BSA_{si} < SW_i \end{cases} \\[2ex] D_{sb} \qquad for\ p = s + 1, q = b + 1 \end{cases} \tag{4-3}$$

The general shape of the variable DA is shown in Figure 4-5.

<table>
<tr><td>Column #
Row #</td><td>1</td><td>$2=b+1$</td><td>…</td><td>$Max\{b\}+1$</td><td>$Max\{b\}+2$</td></tr>
<tr><td>1</td><td></td><td colspan="3">OS_b, $\forall b$</td><td></td></tr>
<tr><td>$2=s+1$</td><td rowspan="3">OS_s, $\forall s$</td><td colspan="3" rowspan="3">D_{sb}, $\forall s,b$</td><td rowspan="3">SQ_{si}, $\forall s,i$</td></tr>
<tr><td>…</td></tr>
<tr><td>$Max\{s\}+1$</td></tr>
</table>

Figure 4-5 General Shape of the Array Variable DA

Use of the 'Search' module in ARENA serves to identify the minimum distance path to ship biomass from a given feedstock supply location to the biorefinery. In simulation trucks are sent to the nearest supply location for a particular feedstock until that location runs out of stock. The binary variable SQ_{si} associated with the matrix variable DA (see Equation 4-3 and Table 4-3) becomes zero at this point, effectively closing the supply location; no further trucks will be sent there for that given day. Subsequently, the next closest supply location is selected for shipments until it is exhausted and so forth. The function of the Search module is summarized by the logic in Figure 4-6.

After all distances in the distance array variable column associated with the optimum biorefinery location have been checked to ensure the closest supply location has been selected, the vector BSA is updated to indicate the removal of biomass from the selected supply location. This is achieved via Equation 4-4 where SW_i is the weight of a shipment of biomass (i). In cases where the biomass amount stored (in the variable BSA) is less than the shipment weight (i.e. shipment from the location will result in a partially filled truck and leave the supply location empty) Equation 4-5 should be employed. Logic in ARENA provides for this decision. Thus, the biomass supply is emptied ($BSA_s = 0$) and the binary variable SQ_{si} in DA (Equation 4-3) is set to zero to indicate no supply. Here again, BSA' represents the updated variable BSA.

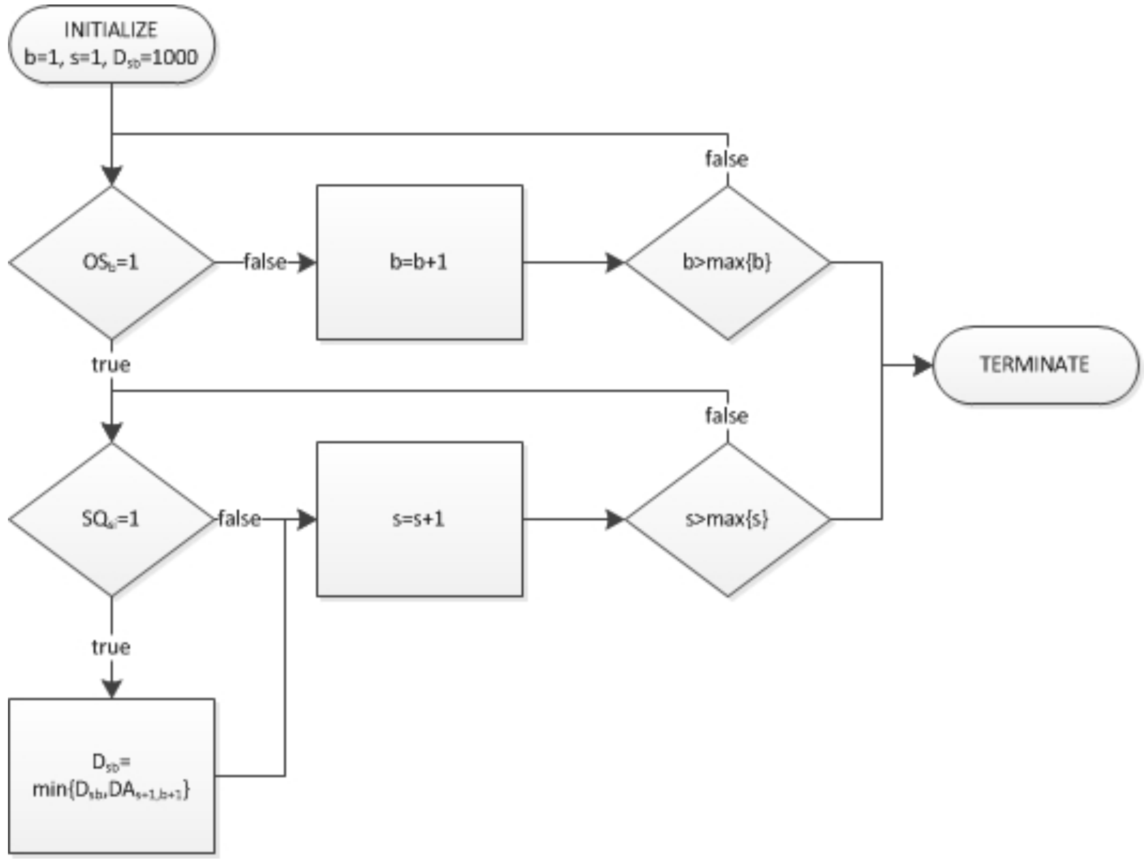


Figure 4-6 Logic to Select Minimum Distance from Supply to Biorefinery Locations

$$BSA'_s = BSA_s - \mathrm{SW_i} \tag{4-4}$$

$$BSA'_s = 0 \tag{4-5}$$
$$SQ_{si} = 0$$

The delivery of biomass to the biorefinery is achieved in simulation through the evaluation of Equation 4-6. Via these equations an updated value of biomass stored at the biorefinery for use in the production of finished goods and utilities, BS_i (with the updated value denoted BS_i'), is calculated. As noted, if the amount of biomass available at supply locations (BSA_{si}) is greater than or equal to the assumed shipment weight of biomass i, then biorefinery stocks are increased by one full shipment. Otherwise, a partially full truck is sent containing the entire stock available at the supply location.

$$BS_i' = BS_i + SW_i\,,\ If \quad BSA_{si} \geq SW_i \tag{4-6}$$

$$BS_i' = BS_i + BSA_{si},,\ If \quad BSA_{si} < SW_i$$

Costs associated with raw material transportation, diesel fuel use (assuming truck transportation), and material cost to the biorefinery for purchase of the biomass should be recorded for the determination of biorefinery supply chain profitability. The first cost is transportation cost (C_T). This value accounts for the time dependent and distance dependent expenses associated with shipping biomass excluding transportation fuel expenses (these are considered separately). Again, the prime denotes updated variables.

$$C_{Ti}' = C_{Ti} + 2*[[D_{s,b} * CPM] + (TC_{BS}(t)/TS)] \tag{4-7}$$

Diesel fuel costs associated with biomass feedstock transport (C_{Di}) are calculated via Equation 4-8 where C_{Di}' is the updated variable. The deterministic parameter TDR is an assumed truck diesel requirement given in units of gallons/ton-mile. Therefore, multiplying this value by twice the distance from the biomass source to the biorefinery (to account for travel to and from the supply location) yields the distance dependent portion of the cost. Additionally, truck and shipment weight (TW and SW_i , respectively) are taken into consideration. Truck weight is considered twice while shipment weight is only added once; this is to simulate truck movement to a feedstock supply location empty and to the biorefinery with a full or partial load.

$$C_{Di}' = C_{Di} + [(DP*TDR)*(2*D_{sb} + 2*TW + SW_i)],\ If\ BSA_s \geq SW_i \tag{4-8}$$

$$C_{Di}' = C_{Di} + [(DP*TDR)*(2*D_{sb} + 2*TW + BSA_{si})],\ If\ BSA_{si} < SW_i$$

Raw material purchase cost is also taken into consideration in simulation. These values, calculated with Equation 4-9, account for the expenses incurred by the biorefinery from procurement of feedstock materials. The assumed per ton price of the biomass feedstock is multiplied by the shipment weight (SW_i) each time a shipment is made.

$$C_{Mi}' = C_{Mi} + (SW_i * MC_i), \qquad If \quad BSA_s \geq SW_i \tag{4-9}$$

$$C_{Mi}' = C_{Mi} + (BSA_s * MC_i), \qquad If \quad BSA_s < SW_i$$

These steps for calculating the various costs, associated with feedstock delivery from supply locations to the biorefinery location are repeated until the condition displayed as Equation 4-10 is satisfied for each biomass raw material (i) under consideration.

$$BS_i \geq DBR_i \quad \forall\ i \tag{4-10}$$

Steps must also be followed for the simulation of product generation, selection of optimal distribution market locations as well as for the delivery of finished biorefinery products to the market.

ARENA decision logic determines the biomass present at the biorefinery and calculates the biorefinery operating costs and storage costs. The biorefinery is not considered to have stored the biomass consumed for a the production of a given days biofuels and other products; at steady state, the biorefinery would consume the raw materials as shipments were received to convert them to finished products. Biorefinery stocks of biomass are reduced by the daily biomass requirements as per Equation 4-11.

$$BS_i' = BS_i - DBR_i \quad \textit{for all biomass sources, } i \tag{4-11}$$

Operating costs are determined based on the assumed costs obtained from the process optimization model. To capture some variability, a triangular distribution has been defined with a range of ± 5% of the assumed operating costs for August (DOC_A) and the remainder of the year ($DOC_{S\text{-}J}$) as per the notation in Table 4-2. This is summarized as Equation 4-12.

$$\begin{gathered} \textit{If } m = \textit{August} \\ C_O = TRIA(DOC_A*(1-0.05),\ DOC_A,\ DOC_A*(1+0.05)) \\ \textit{Else} \\ C_O = TRIA(DOC_{S\text{-}J}*(1-0.05),\ DOC_{S\text{-}J},\ DOC_{S\text{-}J}*(1+0.05)) \end{gathered} \tag{4-12}$$

Storage costs to the biorefinery are considered to be localized to the biomass stored on site after production of the biofuels has occurred. This cost is expressed as Equation 4-13.

$$C_S = SC *(\textstyle\sum_1^i BS_i) \tag{4-13}$$

The variable PSA serves the same role for product supply as BSA did for feedstock supply. The sum of the values of the random variable PD_{jc} (the demand for a product (j) in region (c)) over all months (m) divided by the number of demand locations (d) for product (j) in region (c), n_{djc} for each of the demand locations (d) in region c gives the value for entries in the vector PSA. This is described by Equation 4-14.

(4-14)

$$PSA =< \left(\textstyle\sum_1^m PD_{1,c}\right)/n_{d1c}\,, \forall d, c; \left(\textstyle\sum_1^m PD_{2,c}\right)/n_{d2c}\,, \forall d, c; \dots; \left(\textstyle\sum_1^m PD_{j,c}\right)/n_{djc}\,, \forall d, j, c >$$

Product transportation to market is then modeled in a similar fashion to feedstock transport. Here, Search modules are used to determine the closest product point of sale with unsatisfied demand. The array variable searched has been titled DM and contains information similar to Table 4-3. DM is defined specifically as Equation 4-15 where the subscripts p and q represent the rows and columns of the matrix DM, respectively. The parameter D_{bd} represents the distance from the biorefinery location (b) to the demand locations (d).

$$DA_{pq} = \begin{cases} \boldsymbol{OS_b = \begin{cases} 1, & if\ p = 1, q - 1 = b \in\ optimal\ supply\ chain \\ 0, & if\ p = 1, q - 1 \neq b \in\ optimal\ supply\ chain \end{cases}} \\ OS_d = \begin{cases} 1, & if\ p - 1 = d \in\ optimal\ supply\ chain\ , q = 1 \\ 0, & if\ p - 1 \neq d \in\ optimal\ supply\ chain, q = 1 \end{cases} \\ SQ_{dj} = \begin{cases} 1, & if\ p = d + 1, q = max\ \{b\} + 2\ AND\ PSA_{dj} \geq SW_j \\ 0, & if\ p = d + 1, q = max\ \{b\} + 2\ AND\ PSA_{dj} < SW_j \end{cases} \\ D_{bd} \qquad for\ p = d + 1, q = b + 1 \end{cases} \tag{4-15}$$

The general shape of the variable DM is shown in Figure 4-7.

Column # / Row #	1	*2=b+1*	…	*Max{b} +1*	*Max{b} +2*
1		*OS_b, ∀b*			
2=d+1					
…	*OS_d, ∀d*	*PD_{bd}, ∀b,d*			*SQ_{dj}, ∀d,j*
Max{d}+1					

Figure 4-7 General Shape of the Array Variable DM

Use of the 'Search' module in this instance proceeds in the same fashion as is illustrated in Figure 4-6. In this case, however, instances of the subscript s should be replaced with d and the variable DA should be replaced with DM. With these small modifications, the module works to identify the shortest routings taking into consideration demand.

When a shortest distance path is identified for product transportation, the variable PSA is updated to indicate delivery of the product to the marketplace. In Equations 4-16 and 4-

17 the prime indicates an updated variable. When the product stored is greater than the demand, an amount of product j equal to one shipment is removed from the stock. In contrast, when the stored products are less than demand, all products in storage are delivered for sale and the binary variable SQ_{dj} is set to zero, indicating product j is no longer available for sale.

$$PSA_d' = PSA_d - SW_j,\ If\ PSA_d \geq PD_{jd} \tag{4-16}$$

$$PSA_d'=0,\ If\ PSA_d < PD_{jd} \tag{4-17}$$
$$SQ'_{dj} = 0$$

The delivery of product to market locations results in the variable PMA updating similarly to the variable BS seen previously for biomass feedstock delivery to the biorefinery. Equation 4-18 displays this interaction with the prime indicating updated variables.

$$PMA_j' = PMA_j + SW_j,\ If\ PSA_{dj} \geq SW_j \tag{4-18}$$
$$PMA_j' = PMA_j + PSA_{dj},\ If\ PSA_{dj} < SW_j$$

Product delivery, like feedstock delivery, results in costs for transportation and fuel expenses. These values are calculated in much the same way as their feedstock-related counterparts via Equations 4-19 and 4-20.

$$C_{Tj}' = C_{Tj} + 2*[[D_{b,d} * CPM] + (TC_L(t)/TS)] \tag{4-19}$$

$$C_{Dj}' = C_{Dj} + [(DP*TDR)*(2*D_{bd}+2*TW+ SW_j)],\ If\ PSA_d \geq SW_j \tag{4-20}$$

$$C_{Dj}' = C_{Dj} + [(DP*TDR)*(2*D_{bd}+2*TW+ PSA_{dj})],\ If\ PSA_{dj} < SW_j$$

Following the calculation for costs associated with the transportation of a specific liquid product to a market location, the income variable (I) is updated via Equation 4-21. It should be noted that non-liquid fuel products (i.e. natural gas and electricity) utilize the same income equation; for them, the transportation steps are foregone. Since the shipments of products are made taking into consideration the demand at the market locations, it is assumed that the product delivered to market has a buyer and, therefore, results in income.

$$I' = I + \sum_{1}^{j}[P_j * PMA_j] \tag{4-21}$$

Total cost associated with the supply chain activities of biomass and biorefinery products are calculated via Equation 4-22.

$$Total\ Costs\ = C_O + C_S + \sum_{1}^{i}[C_{Ti} + C_{Di} + C_{Mi}] + \sum_{1}^{i}[C_{Tj} + C_{Dj}] \tag{4-22}$$

The time-value of money is taken into consideration in modeling by employing the discounted cash flow method. In this way, the future profits or losses from the biorefinery supply chain can be accounted for in current common-year dollar values. It is assumed for modeling purposes that an interest rate of 3% per year is reasonable. Through standard unit conversion operations the yearly interest rate can be converted into an equivalent daily rate (r); therefore, the present value of a supply chain design on a given day, t, is found through computation of Equation 4-23:

$$NPV_t\ = NPV_{t-1} + \frac{[Income_t - Total\ Costs_t]}{(1+r)^t} \tag{4-23}$$

Various subsidies have the potential to change supply chain performance. In the model, as per the literature reviewed, subsides are based on a '\$/gallon produced' paradigm wherein biorefineries receive an assumed dollar amount for each gallon of liquid fuel that replaces fossil based fuels in the market place. Subsidies are applied by adding the earned subsidy value for a particular day to that days income, as seen in Equation 4-24.

$$Income_t' = Income_t + \sum_1^j (SR * PSA) \qquad (4\text{-}24)$$

The simulation system clock is then advanced 1 day.

The methodology developed here has been exercised with the application of a case study that will be described in Chapter 5.

5 CASE STUDY DESCRIPTION

In order to demonstrate the simulation model's capabilities, a case study has been developed. The basis for the case study is the optimal supply chain designed by Faulkner (2012) utilizing chemical process information obtained from modeling presented in Sukumara et al (2012). The case study is presented to demonstrate the value of simulation modeling in the context of an integrated biorefinery supply chain decision-making framework.

The case study utilizes data from the Jackson Purchase Region of Kentucky. In order to demonstrate the linkage among various aspects of the integrated biorefinery decision-making framework, it is important to maintain a consistency of data among the models. To this end, data sets used for biomass availability, product demand, and assumed values (from literature) for parameters such as feedstock moisture content, among others, was maintained the same as that used in Faulkner (2012) and Sukumara, et al (2012).

The remainder of this chapter is divided into subsections to facilitate discussion of the case study. Section 5.1 includes details about the case study region. Section 5.2 describes key inputs obtained from the other component models in the overall decision support framework. Section 5.3 focuses on the determination of potential feedstock supply locations and the development of biomass supply distributions. Similarly, Section 5.4 discusses the selection of product market point-of-sale locations as well as the development of daily demand distributions for these locations. Finally, Chapter 5 concludes with Section 5.5 and a discussion of the simulation model implementation.

5.1 Jackson Purchase Region, KY

As indicated in Figure 5-1, the Jackson Purchase Region (JPR) is located in southwest Kentucky and consists of Ballard, Calloway, Carlisle, Fulton, Graves, Hickman, Marshall, and McCracken counties. Figure 5-2 highlights these individual counties as well as the existing regional energy infrastructure.

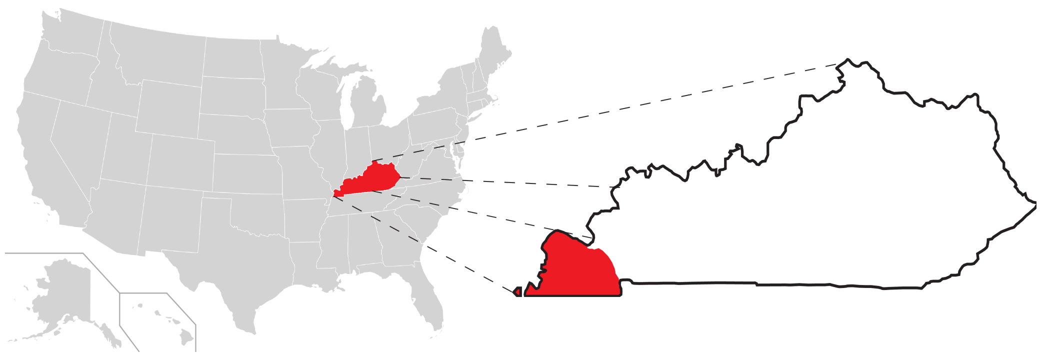


Figure 5-1 Jackson Purchase Region of Kentucky

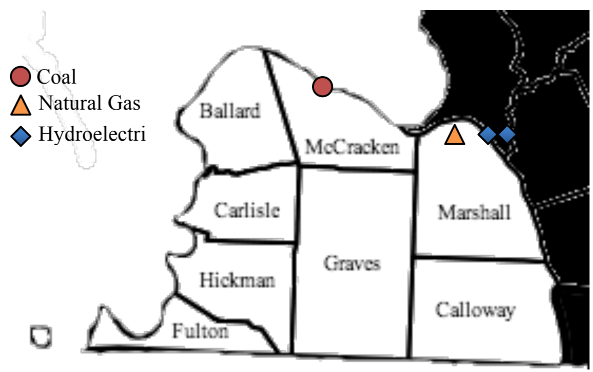


Figure 5-2 JPR Counties and Existing Energy Production Infrastructure

The location was originally chosen due to a combination of factors. First, the variety of potential feedstocks available was a driver for selection. These counties are rural with economies that are largely agriculturally based. This economy provides opportunity to explore uses for non-food biomass sources. The production of corn, soybeans, wheat, and other crops in the region yields a significant potential source of lignocellulosic material in the form of crop residues. A thriving poultry industry and numerous chicken houses led to the notion of exploring spent chicken litter, typically a waste stream, as a potential feedstock for fuel and energy production. Additionally, vicinity of the region to protected forests and wooded areas prompted the decision to consider forest residues as an additional source of raw material for a regional biorefinery. Finally, as highlighted in Figure 5-2, the region is currently home to coal, natural gas, and hydroelectric energy production facilities. This regional expertise and tradition of energy export could provide support for a potential biofuel and energy plant.

With a population of approximately 200,000 (U.S. Census Bureau, 2010) this region also can be assumed to have the necessary supporting infrastructure to support a biorefinery. The JPR has a demand base for the consumption of liquid fuels, natural gas, and electricity produced by the suggested biorefinery. Road transportation networks are well established in the region, making biomass and product trucking feasible. Besides this, the region's borders are composed of major water bodies. The Mississippi river forms the western boundary, the Ohio forms the northern border, and Kentucky Lake / the Tennesse river lie to the east of the region. These waterways are widely used for the transportation of coal via barge in the region; it is not unreasonable to envision similar usage for biomass-based sources of raw materials. In addition to water and road infrastructure, rail transport is available in the region as well.

With this abundance of transportation options, potential feedstock resources, and potential consumers for finished products, the JPR provides an outstanding microcosm for the application of region specific integrated biorefinery supply chain development.

5.2 Inputs from Other Models in the Multidisciplinary Framework

As was previously mentioned, this research focuses on the development of simulation models to be incorporated to the integrated biorefinery decision support framework. As such, it was necessary to utilize several specific outputs from other models in the framework. In addition, several data inputs were common and used across all models including geo-spacially identified potential feedstock supply locations, biorefinery sites, product selection, product conversion rate, and end market demand destinations. All of these inputs were developed in an iterative fashion simultaneously. For discussion, an explanation of each of these inputs is provided in the following subsections.

5.2.1 Inputs from Chemical Processing Simulation and Optimization

Given an initial survey of relevant data for biomass feedstock supply in the region, corn stover, chicken litter and forest residue were selected as the three sources to be considered for integrated biorefining. Then, ASPEN was utilized to design chemical processes for the conversion of these feedstocks to biorefinery products. The technology modeled (as per Sukumara et al (2012)) integrated biorefining including gasification which results in a product rich in CO and H_2 gas known commonly as syngas, a Hydrogen gas-shift reactor which increases the ratio of CO to H_2, and Fischer Tropsch synthesis for the synthesis of gasoline, diesel fuel, residual fuel oil, and natural gas. Electricity, the final product, is produced via combustion of the H_2 following the Hydrogen gas-shift reaction.

Given an initial range for feedstock amounts provided to the biorefinery, ASPEN Economic Optimizer is used to minimize heating utility, cooling utility, and electricity costs. The resulting consumption of feedstock and product output for the marketplace were used as input values for the MILP model (Faulkner, 2012). These results were further optimized through iteration between the MILP model and the ASPEN model; heat integration, wherein existing thermal energy in the system is harnessed to further minimize heating and cooling utility costs, was implemented as well.

Ultimately, plant operating costs, consumption rates for each feedstock, and production rates for each product were obtained and used as assumed parameters in the simulation model. The values obtained from this activity can be seen in Table 5-1.

Table 5-1 Inputs obtained from process simulation and optimization

			Medium Biorefinery		Small Biorefinery	
		Units	Aug	Sept-Jul	Aug	Sept-Jul
Feedstock Requirements	Chicken Litter	Tons/Day	61.96	255.30	59.00	107.30
	Corn Stover		327.70	535.30	218.05	423.57
	Forest Residue		5.77	27.52	11.66	17.46
Operating Cost		$/Day	17,638.22	21,077.73	8,677.25	14,685.39
Production	Gasoline	Gal/Month	57,478	87,469	29,100	54,688
	Diesel		116,066	182,527	56,837	111,100
	Natural Gas		6,390	10,622	2,934	6,153
	Electricity		2,024	3,244	990	1,945
	Residual Fuel Oil		289,792	498,386	147,312	298,867

5.2.2 Inputs from Supply Chain Optimization Modeling

The above inputs were developed in parallel with a MILP model (Faulkner 2012) which uses the results from chemical process simulation. In order to design the supply chain, potential biorefinery locations were selected as the JPR county seats for simplicity. These are shown in Figure 5-2 plotted using Google Maps®. The accompanying table in the figure lists the JPR counties along with their respective county seats.

Based on selected maximum biomass capacity available in the JPR counties, the number of potential biomass supply locations was determined by Faulkner (2012). These same potential biomass source locations were utilized in developing the simulation model in this study. Maps developed using Google Maps® showing locations of potential feedstock supply locations have been adapted from the work of Faulkner (2012) and are presented in Figures 5-4 through 5-6. In the case of chicken litter, previous GIS work (Zhang, 2010) was leveraged as well to generate Figure 5-6.

County	County Seat
Ballard	Wickliffe
Calloway	Murray
Carlisle	Bardwell
Fulton	Hickman
Graves	Mayfield
Hickman	Clinton
Marshall	Benton
McCracken	Paducah

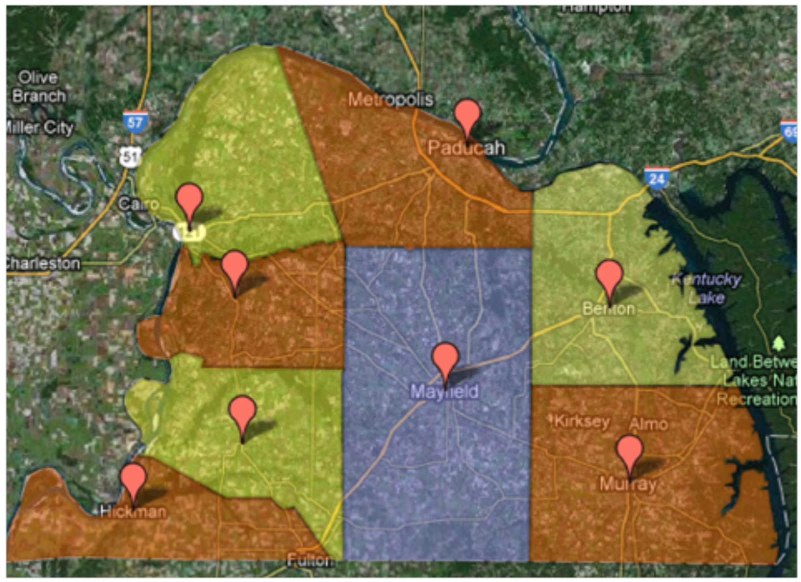


Figure 5-3 Potential Biorefinery Locations in JPR County Seats [Faulkner (2012)]

County	# of CS Locations
Ballard	4
Calloway	3
Carlisle	3
Fulton	4
Graves	7
Hickman	6
Marshall	2
McCracken	2

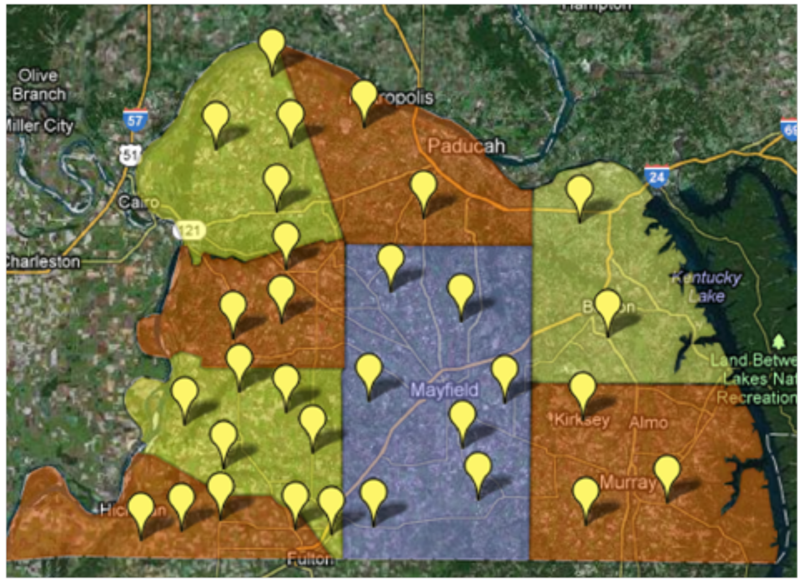


Figure 5-4 Potential Corn Stover Supply Locations in JPR [Faulkner (2012)]

County	# of FR Locations
Ballard	4
Calloway	2
Carlisle	5
Fulton	1
Graves	3
Hickman	1
Marshall	2
McCracken	1

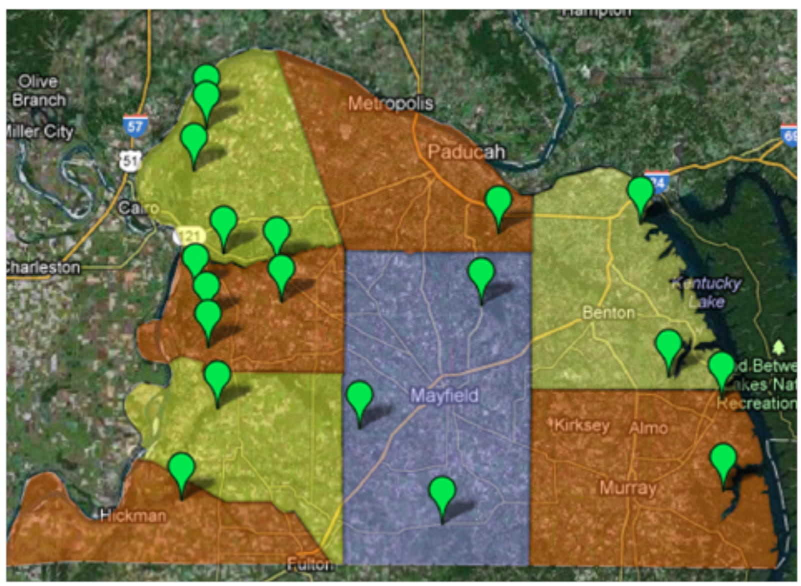


Figure 5-5 Potential Corn Stover Supply Locations in JPR [Faulkner (2012)]

County	# of CL Locations
Ballard	1
Calloway	2
Carlisle	1
Fulton	1
Graves	9
Hickman	6
Marshall	1
McCracken	0

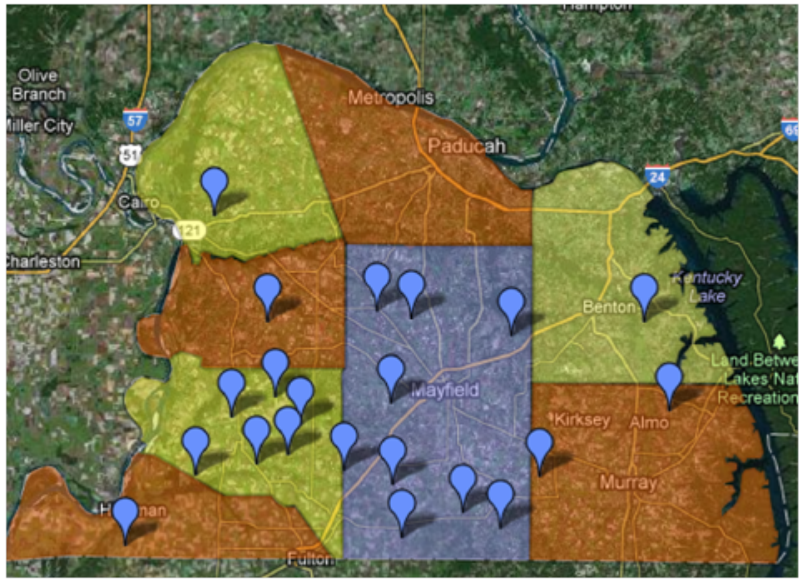


Figure 5-6 Potential Chicken Litter Supply Locations in JPR [Faulkner (2012)]

The distance array (DA) matrix used as input for the simulation model was established using information presented in Figures 5-3 through 5-6. For each feedstock, Appendix B defines the overall distance array (DA) variable (discussed in Chapter 4.2.1.).

Similar to the supply location inputs, point of sale locations for finished product demand have been predetermined by Faulkner (2012) based on a selected optimal product slate determined by Sukumara et al (2012), regional product consumption data, and demographic information related to each county. The products considered in the simulation model include gasoline, diesel fuel, electricity, natural gas, and residual fuel oil. As previously mentioned, the simulation model assumes that electricity is delivered directly to the existing grid and that natural gas is delivered to the market via existing pipeline infrastructure. In both of these cases, the gasoline and diesel points of sale are considered as consumption points; however, transportation costs are not accrued for delivery. For gasoline and diesel fuel, it is reasonable to assume a similar dispensation location, as with nearly any fueling station found in the USA. One market distribution site for these products was selected for each county taking into consideration the county population density; selected locations are at major road crossings in the county seat locations (seen in Figure 5-3). Residual fuel oil, however, has a more specific market. As such, these products should be delivered to existing fuel terminals in the region (IRS 2012).

These same potential points of sale locations were also utilized in the development of inputs for the case study simulation model. A map (developed using Google Maps®) indicating locations of the identified points of sale adapted from Faulkner (2012) is presented in Figure 5-7. The sites for gasoline and diesel sale are indicated with light blue tabs whereas the residual fuel oil locations, both located in McCracken County, are shown with pink markers.

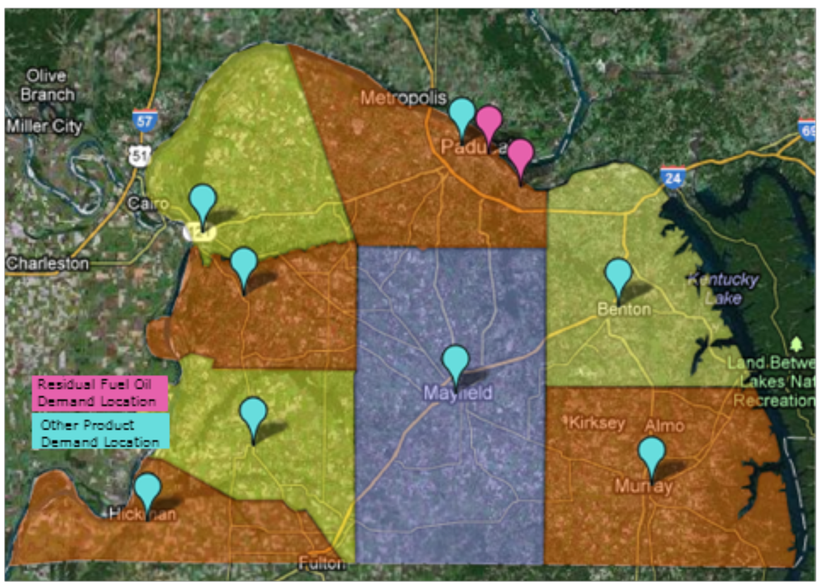


Figure 5-7 Potential Points of Sale in JPR [Faulkner (2012)]

Again, Google Maps' features were used to determine distances among potential biorefinery locations and potential points of sale. These values populated the matrix that describes the variable DM (described in Figure 4-7) and correspond with similar variables found in Faulkner (2012). Table 5-2 defines the overall distance to market array variable with respect to each product. The use of this data is outlined in Chapter 4.1.2.

Table 5-2 Distances between biorefinery and point of sale locations.

Gasoline and Diesel Fuel									
No.	County	Ballard	Calloway	Carlisle	Fulton	Graves	Hickman	Marshall	McCracken
1	Ballard	0.4	54.7	8.9	41.3	30.8	23.8	48.1	32.1
2	Calloway	55.2	0.7	50.6	52.0	24.5	46.0	18.8	47.1
3	Carlisle	8.2	50.1	0.4	32.7	26.3	15.3	43.6	33.9
4	Fulton	42.2	51.5	33.6	0.9	39.8	18.7	58.9	68.9
5	Graves	31.8	23.7	27.3	40.9	0.7	22.2	20.7	29.9
6	Hickman	23.6	43.8	15.0	17.3	23.4	0.1	42.5	49.3
7	Marshall	49.0	18.8	44.4	60.5	20.0	43.0	0.8	24.2
8	McCracken	31.1	52.4	30.0	65.7	26.1	44.9	33.7	2.6
Residual Fuel Oil									
No.	Location	Ballard	Calloway	Carlisle	Fulton	Graves	Hickman	Marshall	McCracken
9	1	34.6	45.7	32.8	68.7	28.2	47.6	27.2	1.3
10	2	43.4	39.5	39.9	64.4	23.8	47.0	22.7	6.1

A crucial output from Faulkner (2012) used as an input for the supply chain simulation model is the optimal supply chain configuration. Faulkner (2012) determined the optimized supply chain for biorefineries of various sizes (described as small, medium, and large based on the volume of biomass feedstock required for operations). Through analysis, it was determined that for the region a ‘large’ size biorefinery is not profitable. Small and medium size facilities, on the other hand, showed the potential for profitability. As such, these two configurations were chosen for simulation modeling. The optimal supply chain configurations adapted from Faulkner (2012) and modeled via simulation can be seen in Figure 5-8.

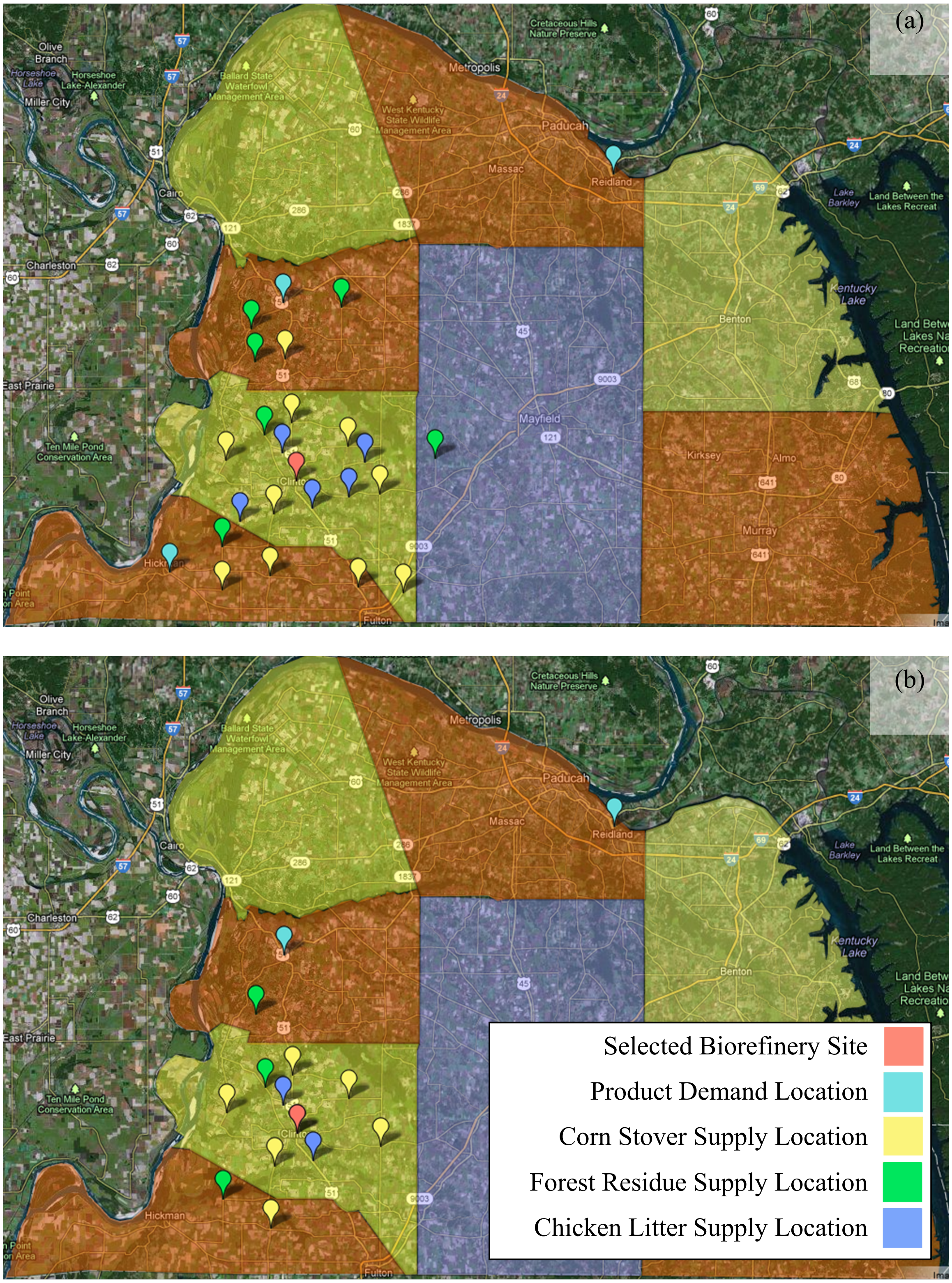


Figure 5-8 Optimal SC for Medium Plant Size (a) and Small Plant Size (b) [Faulkner (2012)]

The configurations from Faulkner (2012) are translated into the values of the binary variable OS_s and OS_d in the array variables DA and DM, respectively, as outlined in Figure 4-5 and Figure 4-7. These values indicate the supply and demand locations that comprise the identified optimal supply chain. Similarly, the binary variable, OS_b (as seen in Figures 4-5 and 4-7) is informed by the choice of optimal biorefinery as selected by Faulkner (2012). The distance information and optimal supply chain information constitute the primary simulation model input obtained from the supply chain optimization model. These factors are used to help explain increases in costs seen by the supply chains over time as they are forced to deviate from their optimal supply chain feedstock sources.

5.3 Biomass Feedstock Related Information

The biomass sources selected for simulation included corn stover, chicken litter, and forest residue based on an initial survey of the regional availability of various biomass in the case study area by Faulkner (2012). In this section, assumptions and details relating to the development of distributions for feedstock supply is discussed.

5.3.1 Corn Stover Input Distributions

Crop residues, in general, are touted as a potential source for lignocellulosic biomass to produce alternative fuels due to their relatively low cost and availability nationally (US DOE, 2011). More specifically, corn stover, the portion of a corn stalk left in the field after harvesting the grain, has been supported as a potential source of raw material due to its relative abundance and, with proper management, ability to be collected with minimally negative impacts on soil erosion (Graham et al, 2007).

For modeling, several assumptions were made regarding corn stover as a feedstock. These are tabulated in Table 5-3 and are consistent with assumptions made by Faulkner, 2012. The data is obtained from Millbrandt (2005).

Table 5-3 Assumed corn stover parameter values

	Assumed Value
Moisture Content	15.5%
Bulk Density of Grain	56 lbs/bushel
Mass ratio (Residue : Grain)	1 : 1

It was additionally assumed that corn stover harvest proceeded at the same time as grain harvest. One pass harvesting has been shown to be technically feasible with moderate modification to traditional corn harvesting equipment (Shinners et al, 2007) and potentially economically superior (Atchison and Hettenhaus, 2004). This assumption greatly simplifies the collection of biomass availability data.

Annual availability of corn stover was determined utilizing publically available county level data related to the percentage of corn harvest completion and corn production (USDA, 2010b and USDA, 2010a, respectively). These data were synthesized according to Equations 5-1 through 5-3 to decompose county level yearly data into weekly corn stover harvest information. This synthesis was carried out for all available years' county level data and the resulting processed data points can be seen in Appendix A. ARENA Input Analyzer was then used to determine monthly corn stover production distribution functions for each county. It should be noted that in some instances, corn harvest data reported for a particular year was revised and these revisions were reported with the subsequent year. These duplicate years' data were included in the analysis to add more data points to the set. Since the system under consideration is extremely variable and the goal of distribution fitting is merely to generate historically reasonable numbers (not to recreate the past exactly) this action was considered reasonable. The generated county level monthly distributions are listed in Table 5-4. These distributions generate new daily corn stover supply; weekly data synthesized using Equations 5-1 through 5-3 are divided by seven to obtain daily values for new corn stover supply at the county level. These daily county values are then evenly distributed among the potential corn stover supply locations as discussed in Chapter 4.

$$\text{corn harvested to date} = \text{total corn to be harvested} \times \%\ \text{harvest complete} \qquad (5\text{-}1)$$

$$\%\ \text{new harvest} = \qquad (5\text{-}2)$$
$$\frac{\text{corn harvested to date on week i} - \text{corn harvested to date on week i}{-}1}{\text{corn harvested to date on week i}}$$

$$\frac{\text{Corn Production (Bu)}}{\text{year}} \times \frac{\text{56 lbs Corn}}{\text{1 Bu Corn}} \times \frac{\text{1 lb Corn Stover}}{\text{1 lb Corn}} \qquad (5\text{-}3)$$

$$\times\ 1.155 \times \%\ \text{new harvest} = \frac{\text{Wet CS harvested}}{\text{week}-\text{county}}$$

In general, the distributions developed produce corn stover supply levels comparable to the historic data quite well as can be seen in Figures 5-3 through 5-10. In some cases, such as for November harvests in Ballard, Calloway, Fulton, and McCracken counties, the range of standard deviations of the distribution expected value and the historic data do not overlap. In these instances, the distribution typically overestimates the corn stover production. These expected values result from relatively small data sets with high variance among the data points. These distributions were allowed to remain in the model, however, as a means to counteract a general tendency of several distributions to underestimate the corn stover supply in August and October. It is important to reiterate the goal of these distribution models. They must produce random values for the variables associated with feedstock supply and the values they produce must be reasonable for the region under investigation. This has been achieved.

Table 5-4 Distributions for Daily Corn Stover Supply Generation

Month	County	Distribution
August	Ballard	((-0.001 + 29300*BETA(0.85, 42.1)))/7
	Calloway	((-0.001 + 29300*BETA(0.85, 42.1)))/7
	Carlisle	((-0.001 + EXPO(3700)))/7
	Fulton	((-0.001 + 29300 * BETA(0.85, 42.1)))/7
	Graves	((-0.001 + EXPO(9710)))/7
	Hickman	((-0.001 + EXPO(6590)))/7
	Marshall	((-0.001 + EXPO(1860)))/7
	McCracken	((-0.001 + EXPO(1860)))/7
September	Ballard	((-0.001 + WEIB(16100, 4.36)))/7
	Calloway	((-0.001 + WEIB(16100, 4.36)))/7
	Carlisle	((3850+20600*BETA(1.35,2.84)))/7
	Fulton	((-0.001 + WEIB(16100, 4.36)))/7
	Graves	((9610+57300*BETA(1.36,3.28)))/7
	Hickman	((7140+38600*BETA(1.15,2.61)))/7
	Marshall	((1390 + 8000*BETA(1.31, 2.83)))/7
	McCracken	((1580+13200*BETA(1.09, 2.16)))/7
October	Ballard	((-0.001 + 29300*BETA(0.662, 3.57)))/7
	Calloway	((-0.001 + 29300*BETA(0.662, 3.57)))/7
	Carlisle	((1690+EXPO(5570)))/7
	Fulton	((-0.001 + 29300 * BETA(0.662, 3.57)))/7
	Graves	((4500+40500*BETA(0.507,0.986)))/7
	Hickman	((3200+GAMM(17200,0.582)))/7
	Marshall	((671 + WEIB(1840, 0.821)))/7
	McCracken	((TRIA(0.001,697,1390)))/7
November	Ballard	((NORM(2120, 462)))/7
	Calloway	((NORM(2120, 462)))/7
	Carlisle	((-0.001+5590*BETA(1.6,2.71)))/7
	Fulton	((NORM(2120, 462)))/7
	Graves	((TRIA(-0.001, 2780,12700)))/7
	Hickman	((TRIA(-0.001, 1390, 9760)))/7
	Marshall	((788+EXPO(3350)))/7
	McCracken	((NORM(1140, 592)))/7

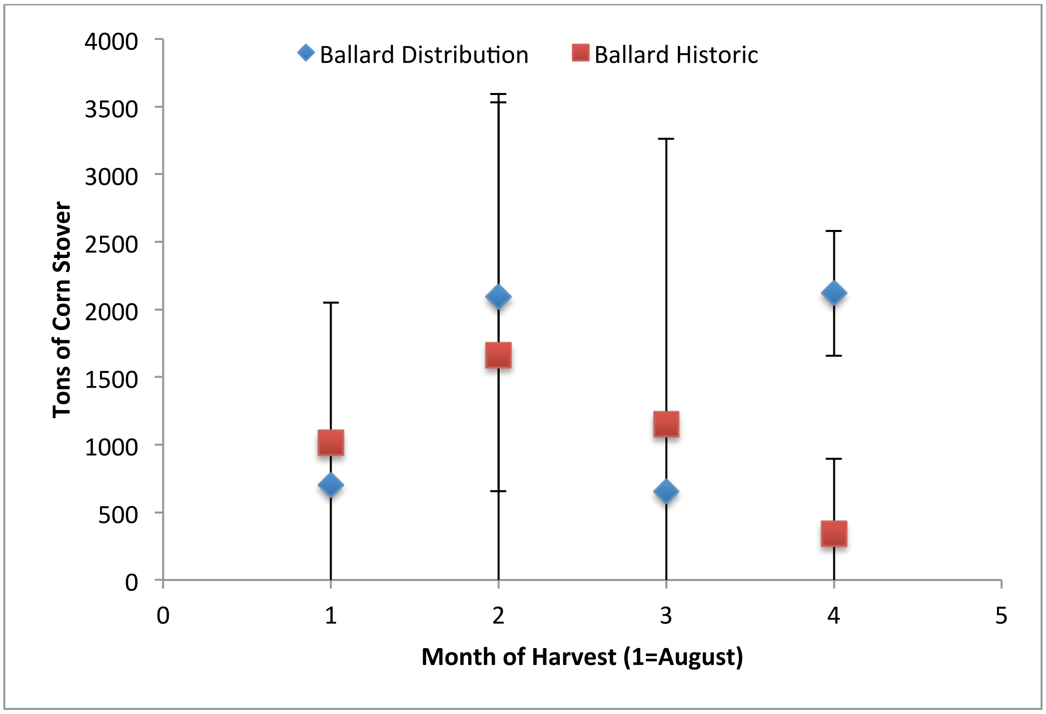


Figure 5-9 CS Distribution Expected Value & Historic Mean – Ballard County

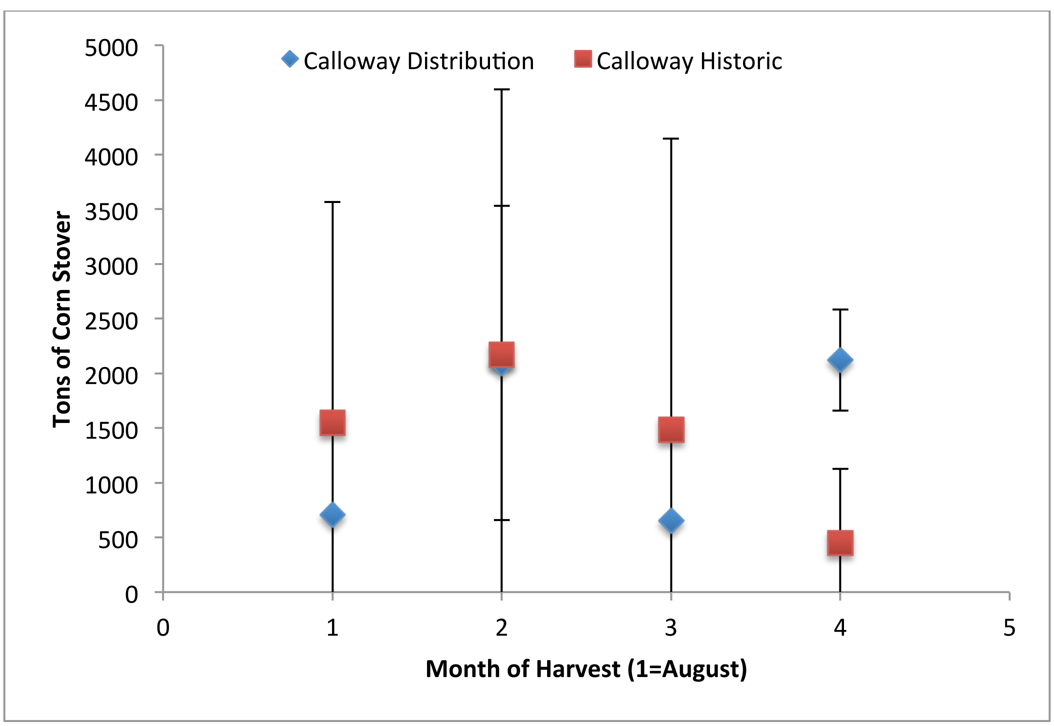


Figure 5-10 CS Distribution Expected Value & Historic Mean – Calloway County

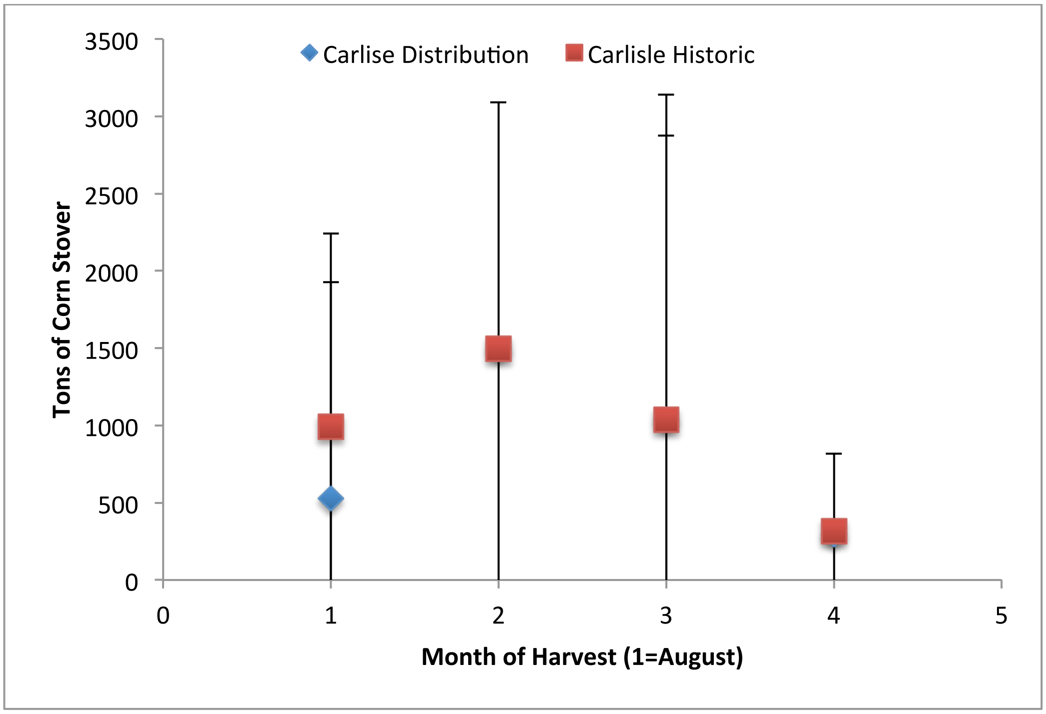


Figure 5-11 CS Distribution Expected Value & Historic Mean– Carlisle County

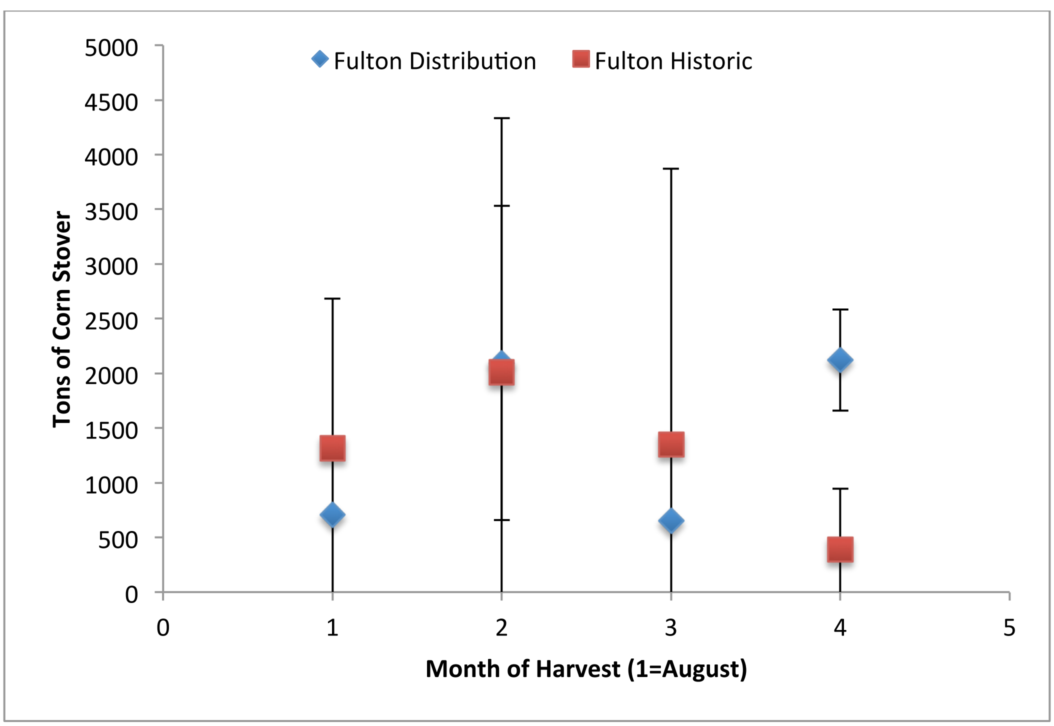


Figure 5-12 CS Distribution Expected Value & Historic Mean– Fulton County

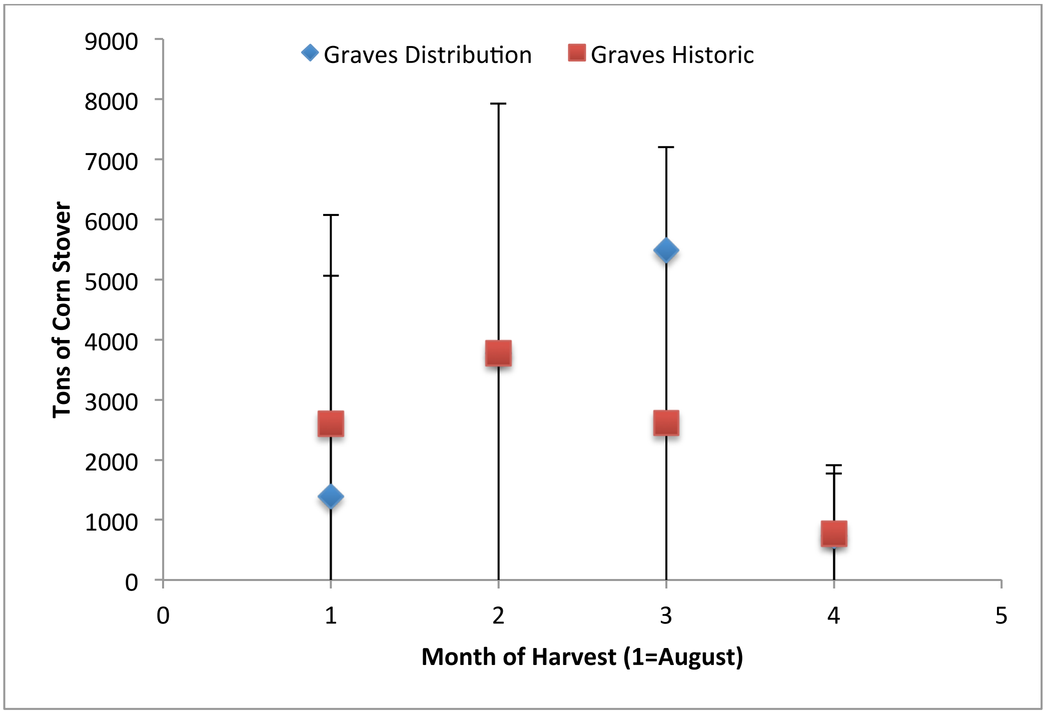


Figure 5-13 CS Distribution Expected Value & Historic Mean– Graves County

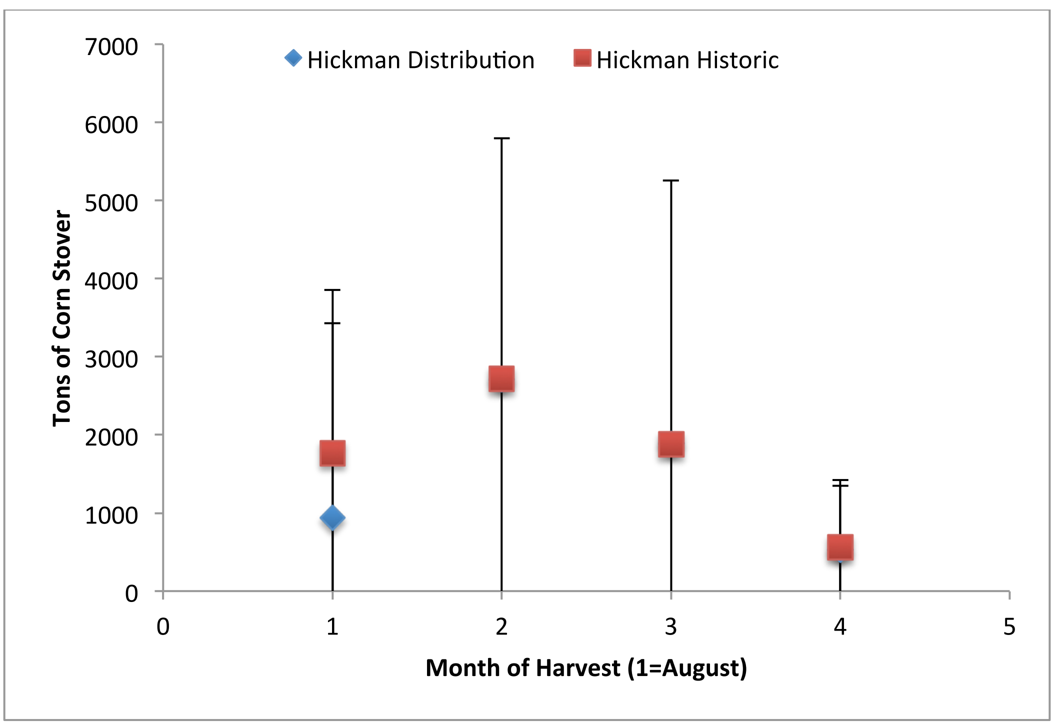


Figure 5-14 CS Distribution Expected Value & Historic Mean– Hickman County

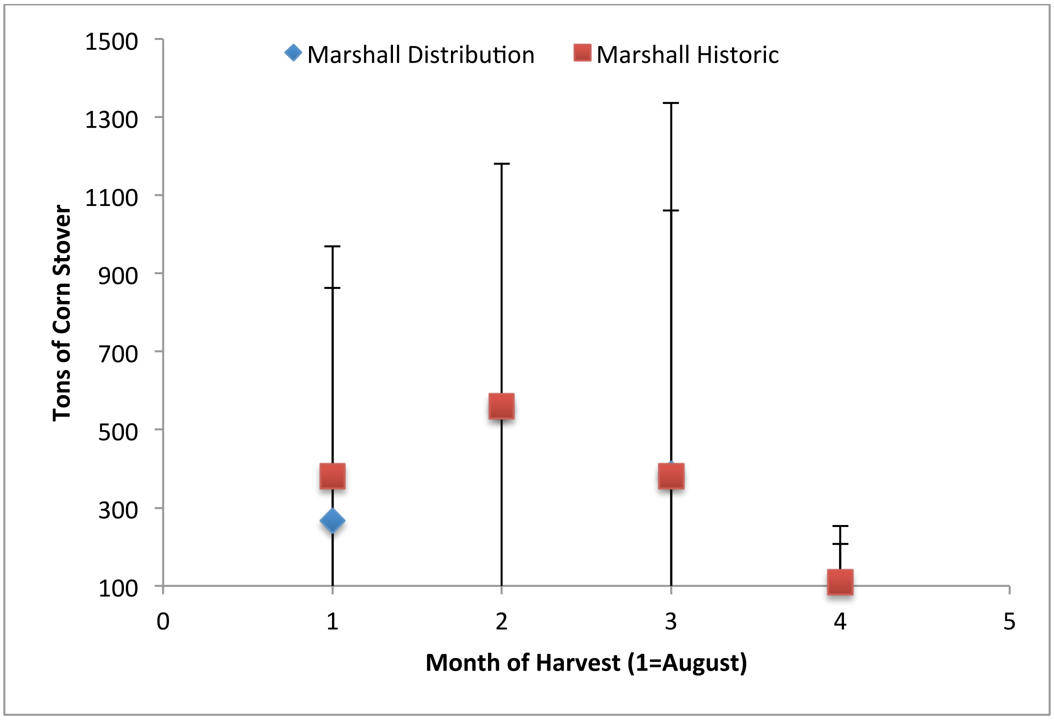


Figure 5-15 CS Distribution Expected Value & Historic Mean– Marshall County

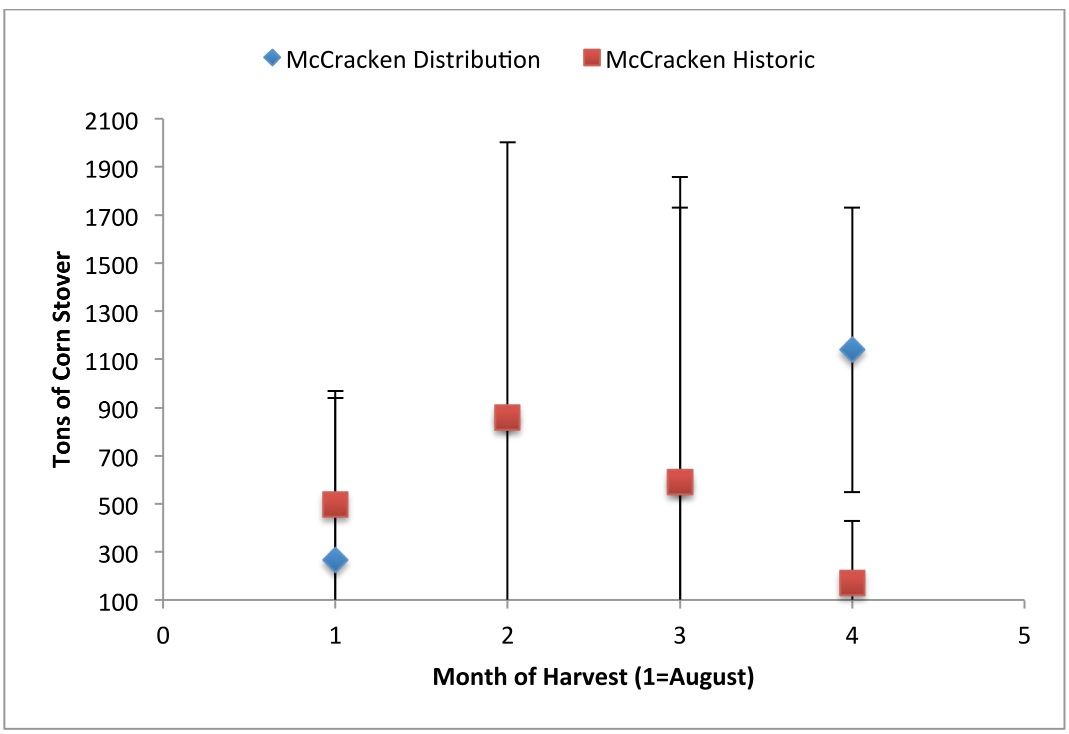


Figure 5-16 CS Distribution Expected Value & Historic Mean– McCracken County

5.3.2 Forest Residue Input Distributions

Defined as the treetops, branches, stumps, dead wood, small-diameter wood, and undergrowth unsuitable for saw logs, forest residue is often removed by forestry officials as a means to minimize risk of catastrophic forest fire (US DOE, 2011). With proper management, improved lifecycle environmental performance relative to other biomass options could be realized by combining residue collection with existing operations (Williams et al, 2009) It should be noted that only sustainable forestry practices should be followed; too aggressive removal can have detrimental effects on the forest system (Hacker, 2005).

Publically available data related to the production of forest residue is much less available than was the case for corn stover. In this case, the Timber Product Output Report provides biannual commercial logging residues volumetrically (TPO, 2009). Since the RFS 2 (US EPA, 2007) does not consider forest residue from federal land “renewable,” forest residues from these sources are not considered in this study. It is assumed that the TPO Report, similarly to Faulkner (2012), represents total forest residue availability in the JPR.

Additionally, for modeling, further assumptions were made regarding forest residue as a feedstock. These can be seen in Table 5-5 and are consistent with assumptions made by Faulkner, 2012.

Table 5-5 Assumed forest residue parameter values and sources

	Assumed Value	Source
Moisture Content	49%	Miles et al, 1995
Bulk Density of Grain	25.6 lbs/ft^3	Brown, 2003

The raw data used for forest residue supply data distribution development, taking into consideration the assumptions mentioned, can be seen in Table 5-6.

Table 5-6 Annual Forest Residue in Jackson Purchase Region

	Annual Logging Residues (Wet Tons)							
Year	Ballard	Calloway	Carlisle	Fulton	Graves	Hickman	Marshall	McCracken
2001	3,098	6,528	9,779	3,379	10,701	2,522	8,102	4,736
2003	9,203	10,176	11,558	3,904	14,976	2,790	8,896	1,600
2005	8,589	7,757	16,448	3,571	14,618	6,874	6,733	3,123
2007	13,146	8,755	14,976	1,830	9,766	4,915	7,987	2,010
2009	17,318	7,283	24,230	2,624	10,803	3,277	9,178	1,997

The Kentucky Division of Forestry recommends that woody biomass harvest should be conducted in conjunction with traditional harvest and forest management activities. The group also suggests that these harvest operations should be timed to avoid logging in wet soil conditions in order to minimize site degradation via soil compaction and rutting (KDF 2011). To maintain this condition it has further been assumed that the entire logging residue is removed within the three driest months in the Jackson Purchase Region. This led to the equal distribution of the values in Table 5-6 across July, August, and September. The resulting monthly values can be seen in Table 5-7.

Table 5-7 Monthly Forest Residue Harvest (July, Aug, and Sep)

	Monthly, Harvested July, Aug, Sep (Wet Tons)							
Year	Ballard	Calloway	Carlisle	Fulton	Graves	Hickman	Marshall	McCracken
2001	1,032.53	2,176.00	3,259.73	1,126.40	3,566.93	840.53	2,700.80	1,578.67
2003	3,067.73	3,392.00	3,852.80	1,301.33	4,992.00	930.13	2,965.33	533.33
2005	2,862.93	2,585.60	5,482.67	1,190.40	4,872.53	2,291.20	2,244.27	1,041.07
2007	4,381.87	2,918.40	4,992.00	610.13	3,255.47	1,638.40	2,662.40	669.87
2009	5,772.80	2,427.73	8,076.80	874.67	3,601.07	1,092.27	3,059.20	665.60

ARENA Input Analyzer was again used to fit the monthly data in Table 5-7 to monthly distribution functions for each county. The generated county level distributions for the months under consideration (July, August, and September) are listed in Table 5-8. The generation of multiple uniform distributions from the data can be taken as an indication of the supply uncertainty in any given month due to the relatively small data set available for distribution development. These distributions generate new monthly forest residue supply. It is assumed that the forest residue harvest is spread evenly throughout the months and, therefore, the generated new forest residue on a given day is equal to the generated monthly value divided by the number of days in the current month. These daily values are distributed evenly among the county forest residue supply locations as discussed in Section 4.

Table 5-8 Distributions for Monthly Corn Stover Supply Generation

County	Distribution
Ballard	UNIF(1.03e+003,5.77e+003)
Calloway	UNIF(2.18e+003,3.39e+003)
Carlisle	(3.26e+003)+EXPO(1.87E+003)
Fulton	UNIF(610,1.3e+003)
Graves	3.26e+003+1.74e+003*BETA(.065,.0757)
Hickman	840+WEIB(361,0.546)
Marshall	UNIF(2.24e+003,3.06e+003)
McCracken	(533+WEIB(265,0.564))

These distributions produce forest residue supply levels similar to the historic data. This comparison can be examined in Figure 5-17. It should be noted that these distribution expected values and standard deviations are based on very limited data input. The distributions reproduce the average historical data very well; additional data would likely increase the standard deviation bars seen in Figure 5-17. At that point, it would be appropriate to re-establish the forest residue supply generation distributions. However, with the limited data available, these distributions suffice.

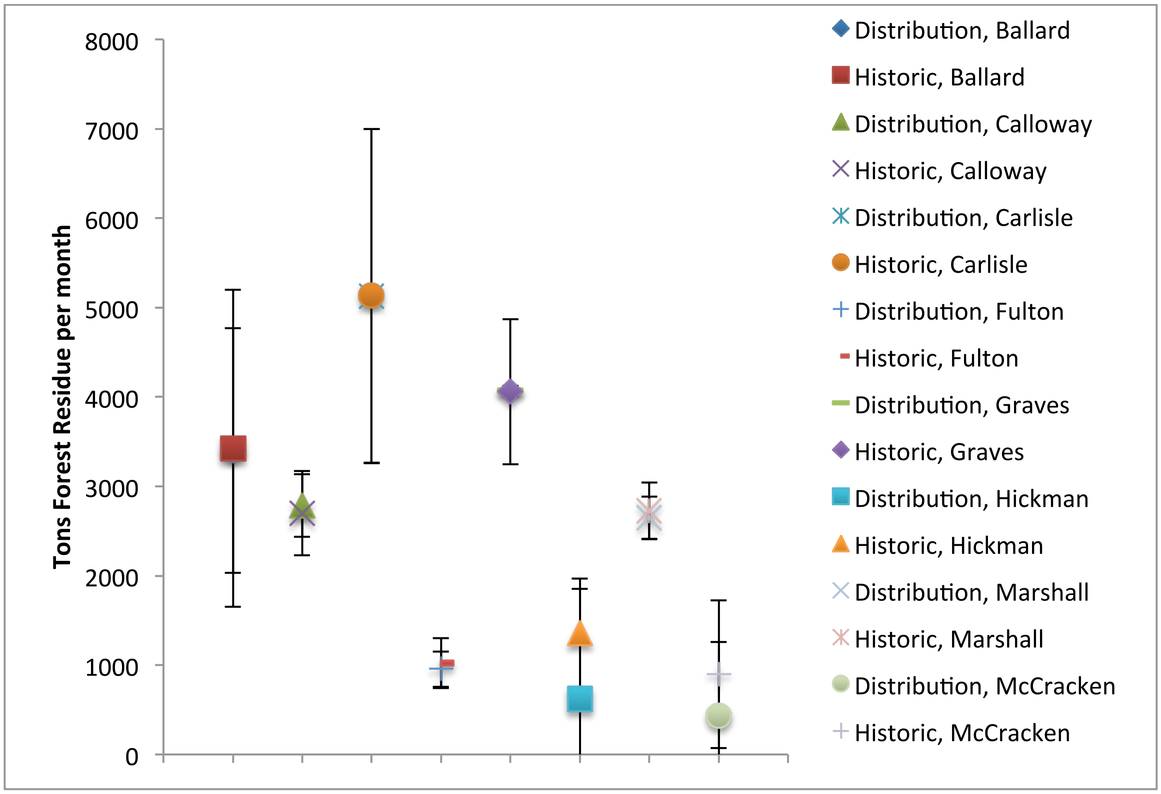


Figure 5-17 Forest Residue Distributions' Expected Values and Historic Means

5.3.3 Chicken Litter Input Distributions

Chicken litter, or more generally poultry litter, consists of bedding material, usually composed of wood chips or shavings, droppings, and other waste materials such as dead birds, feathers, feed and supplements. After its use, several routes for chicken litter disposal exist besides landfilling the material. Chicken litter is often composted, a process of aerobic degradation lasting about a month and yielding fertilizing material for agricultural processes. However, ammonia loss during composting can lead to nutrient poor composted material; in addition, high levels of phosphorus in the poultry litter can have eutrophic effects on local water supplies (Howry et al, 2008). Another method of disposal is anaerobic digestion. Through this process, microbial organisms first degrade lipids and polysaccharides via hydrolysis. The resulting chemical subunits then undergo fermentation or other metabolic processes that convert them into simpler organic compounds. The organic material primarily yields methane, carbon dioxide, and a residual sludge often used as a fertilizer. Another disposal option is direct combustion to produce heat and power (Kelleher et al, 2002). Besides these alternatives, it has been suggested that poultry litter could make a good raw material for fuel and chemical production through experimental work (Dávalos et al, 2002; Kim et al, 2009; Mante and Agblevor, 2011). Among the advantages of this route is the positive utilization of a current waste stream.

Publically available data for end-of-year inventory of broilers (chickens for meat production) and layers (chickens for egg production) were collected. This information is made available every five years by the USDA (2007). Utilizing an assumed manure rate, the generation of the feedstock was determined. Generally, all poultry bedding in use will not be disposed of at one time. Poultry farmers often lay fresh bedding once per year accompanied by a complete cleanout of the houses. They may, in the interim, remove caked material from the houses and add fresh bedding to the top layer of the chicken house (Flora 2006). There has been some controversy regarding the optimal timing for chicken litter disposal (Edwards 1992). For the purposes of this simulation, it has been assumed that some chicken litter is available each month due to the partial cleaning activities. Large quantities of the material become available in December when the full house cleanouts are assumed to occur. The county level chicken inventories are used in conjunction with the assumed manure rate to determine available supply of chicken litter. A lack of reported data for McCracken County leads to its omission from analysis. A constant manure rate and moisture content were assumed from literature; these values can be seen in Table 5-9. This processed data can be seen in Table 5-10.

Table 5-9 Assumed chicken litter parameter values

	Assumed Value	Source
Moisture Content	20%	Miles et al, 1995
Manure Rate	0.04 kg dry matter/head-day	Brown, 2003

Table 5-10 Monthly Chicken Litter Supply Data

Year	County	Chicken Inventories	Chicken Litter Produced	
			Jan-Nov	Dec
2007	BALLARD	971636	653.33	12308.80
	CALLOWAY	1269775	853.33	16076.80
	CARLISLE	863058 43284	586.67 40.00	11052.80 753.60
	FULTON	656514 64220	440.00 53.33	8289.60 1004.80
	GRAVES	8510360 242910	5680.00 173.33	107011.20 3265.60
	HICKMAN	5657755 113016	3773.33 80.00	71089.60 1507.20
	MARSHALL	817355 1041	546.67 13.33	10299.20 251.20
2002	BALLARD	1361131	920.00	17332.80
	CALLOWAY	1569250 786	1053.33 13.33	19844.80 251.20
	CARLISLE	623951	426.67	8038.40
	FULTON	593872 107275	400.00 80.00	7536.00 1507.20
	GRAVES	6198054 235318	4133.33 160.00	77872.00 3014.40
	HICKMAN	3935000 70026	2626.67 53.33	49486.40 1004.80
	MARSHALL	1067857	720.00	13564.80
1997	BALLARD	742200	506.67	9545.60
	CALLOWAY	1953813 258	1306.67 13.33	24617.60 251.20
	CARLISLE	509000 50006	346.67 40.00	6531.20 753.60
	GRAVES	5111998 108238	3413.33 80.00	64307.20 1507.20
	HICKMAN	2094024	1400.00	26376.00
	MARSHALL	567809	386.67	7284.80

Distributions fit to the data for the months January through November as well as for December (when full chicken house cleanout takes place) are shown in Table 5-11. As with the other feedstocks, these production values are distributed evenly across the days of the month and among the county chicken litter supply source locations. Due to the relatively small sample size, the distributions generated are all triangle distributions; these provide a view of the data, however, do not precisely replicate the input observations necessarily. In the case of biorefinery supply chains, where large variability is expected, distribution precision is not necessarily important however.

Table 5-11 Distributions for Monthly Chicken Litter Supply Generation

Month	County	Distribution
January - November	Ballard	TRIA(633,685,1150)
	Calloway	TRIA(1070,1120,1650)
	Carlisle	TRIA(483,513,784)
	Fulton	TRIA(600,602,617)
	Graves	TRIA(4370,4660,7320)
	Hickman	TRIA(1750,2060,4820)
	Marshall	TRIA(483,525,900)
	McCracken	N/A
December	Ballard	TRIA(119000,12900,2.17000)
	Calloway	TRIA(20100,21200,31100)
	Carlisle	TRIA(9110,9670,14800)
	Fulton	TRIA(11298,11300,11600)
	Graves	TRIA(82300,87800,138000)
	Hickman	TRIA(33000,38700,90700)
	Marshall	TRIA(9110,9890,17000)
	McCracken	N/A

In Figure 5-18 the historic mean and simulation values are compared. It should be noted that although the distributions are triangular, the simulation recreates the historical observations well for all counties in January through November.

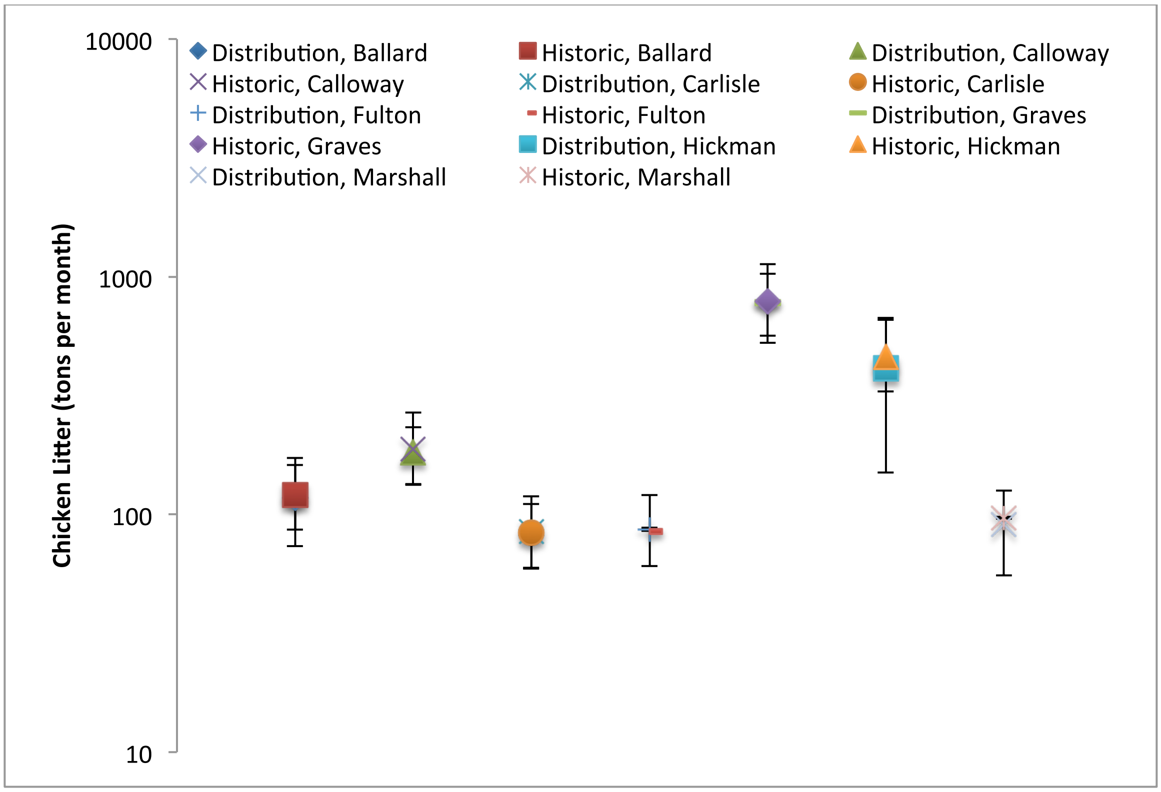


Figure 5-18 Chicken Litter Distribution Expected Value & Historic Mean- Jan-Nov

More variability is observed in December, however (Figure 5-19 and Figure 5-20) due to widely variable historic data. In some cases the simulated values will over or underestimate the supply availability for chicken litter in the county. In general, however, the historic mean is within one standard deviation of the data distribution expected value. Because of this, the simulated values are considered to be reasonable. Clearly, additional data availability would reshape the distributions and provide a more complete representation of the availability of this biomass feedstock.

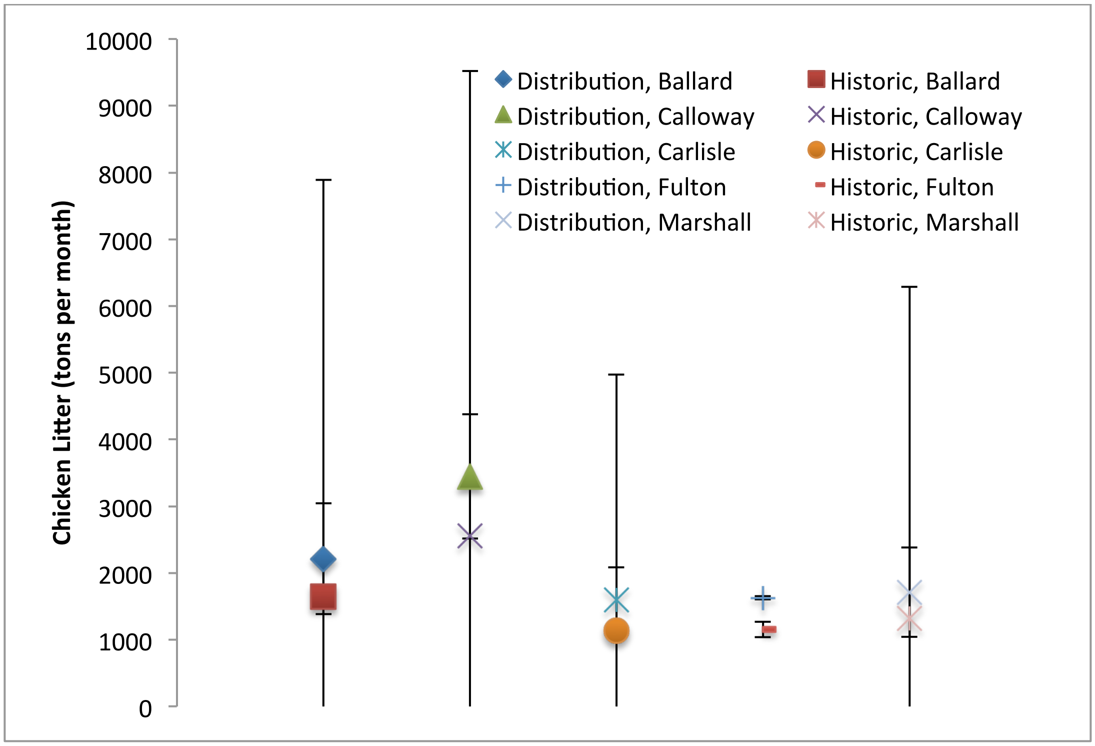


Figure 5-19 CL Distribution Expected Value & Historic Mean- Dec

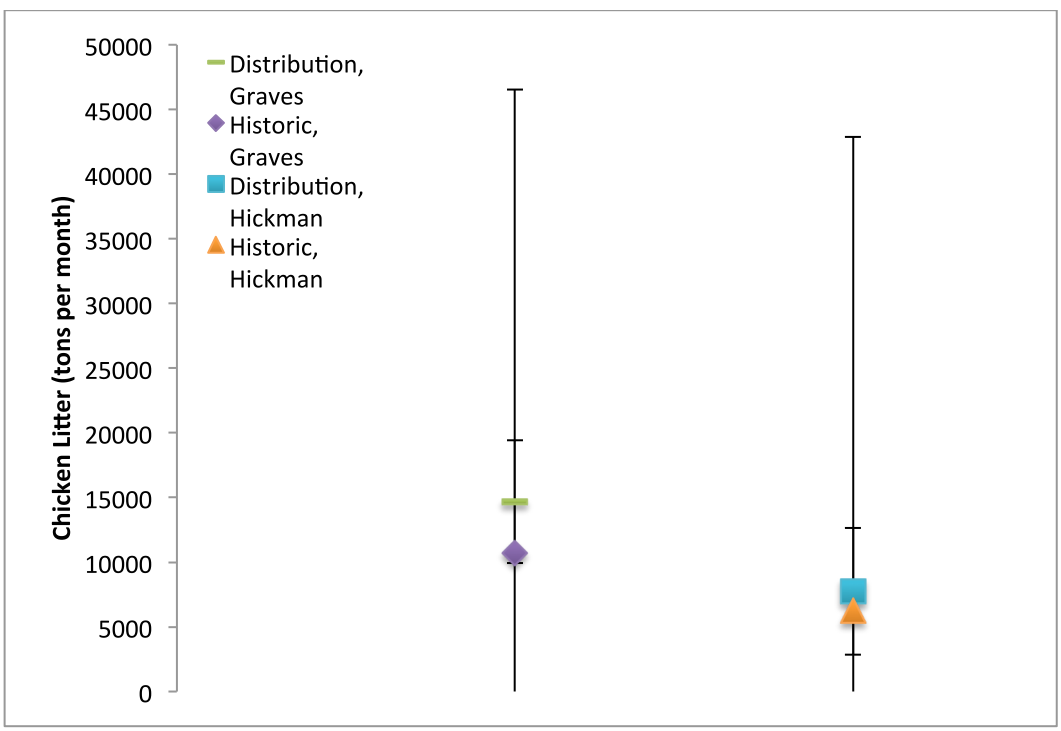


Figure 5-20 CL Distribution Expected Value & Historic Mean- Dec, concluded

5.4 Biorefinery Product Distribution Details

The biorefinery products selected for simulation included gasoline, diesel fuel, residual fuel oil, electricity, and natural gas based input parameters used by Faulkner (2012) and the optimal product portfolio determined by Sukumara et al (2012). Once biomass is available at the biorefinery, production of products is simulated via the values obtained from process modeling found in Table 5-1. Data distributions were created for the demand of each product based on publically available consumption data. This section will highlight the assumptions and details relating to the simulation of biorefinery product demand.

5.4.1 Gasoline Demand Generation

Kentucky gasoline sales from August 2004 to July 2011 (US DOT 2011) were gathered and converted, on a per capita basis, to JPR county level data using the methodology outlined by Faulkner (2012). The averages of the resulting data set can be seen in Table 5-12.

Table 5-12 Average JPR gasoline consumption – [Gallons x 1,000,000]

County	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Ballard	0.32	0.35	0.34	0.37	0.36	0.38	0.37	0.36	0.36	0.34	0.36	0.38
Calloway	1.40	1.53	1.51	1.63	1.59	1.66	1.65	1.59	1.57	1.50	1.56	1.68
Carlisle	0.20	0.22	0.22	0.23	0.23	0.24	0.24	0.23	0.23	0.22	0.23	0.24
Fulton	0.27	0.29	0.29	0.31	0.30	0.32	0.32	0.31	0.31	0.29	0.30	0.32
Graves	1.44	1.58	1.56	1.69	1.65	1.72	1.71	1.66	1.64	1.57	1.62	1.74
Hickman	0.19	0.21	0.20	0.22	0.22	0.23	0.22	0.22	0.22	0.21	0.21	0.23
Marshall	1.20	1.32	1.30	1.40	1.37	1.43	1.42	1.38	1.36	1.30	1.34	1.44
McCracken	2.51	2.75	2.71	2.94	2.87	2.99	2.97	2.88	2.84	2.72	2.82	3.02

Relatively similar consumption within groups of counties was observed in the data. These groups are highlighted via different color shading in Table 5-12. These county level data were aggregated to create combined distributions to simplify data development. ARENA Input Analyzer was utilized to fit the aggregated data sets to distribution functions. These are listed for each county in Table 5-13. It will be observed that the counties grouped in Table 5-12 share common distribution functions.

Table 5-13 Gasoline Demand Distributions

Month	County	Distribution
January - December	Ballard	1.68e+005+GAMM(4.55e+004,2.27)
	Calloway	NORM(1.51e+006,1.61e+005)
	Carlisle	1.68e+005+GAMM(4.55e+004,2.27)
	Fulton	1.68e+005+GAMM(4.55e+004,2.27)
	Graves	NORM(1.51e+006,1.61e+005)
	Hickman	1.68e+005+GAMM(4.55e+004,2.27)
	Marshall	NORM(1.51e+006,1.61e+005)
	McCracken	NORM(2.82e+006,2.04e+005)

The developed distribution performance relative to the historical data means can be seen in Figure 5-21. The grouped county data means fall within the standard deviation of the aggregated distributions.

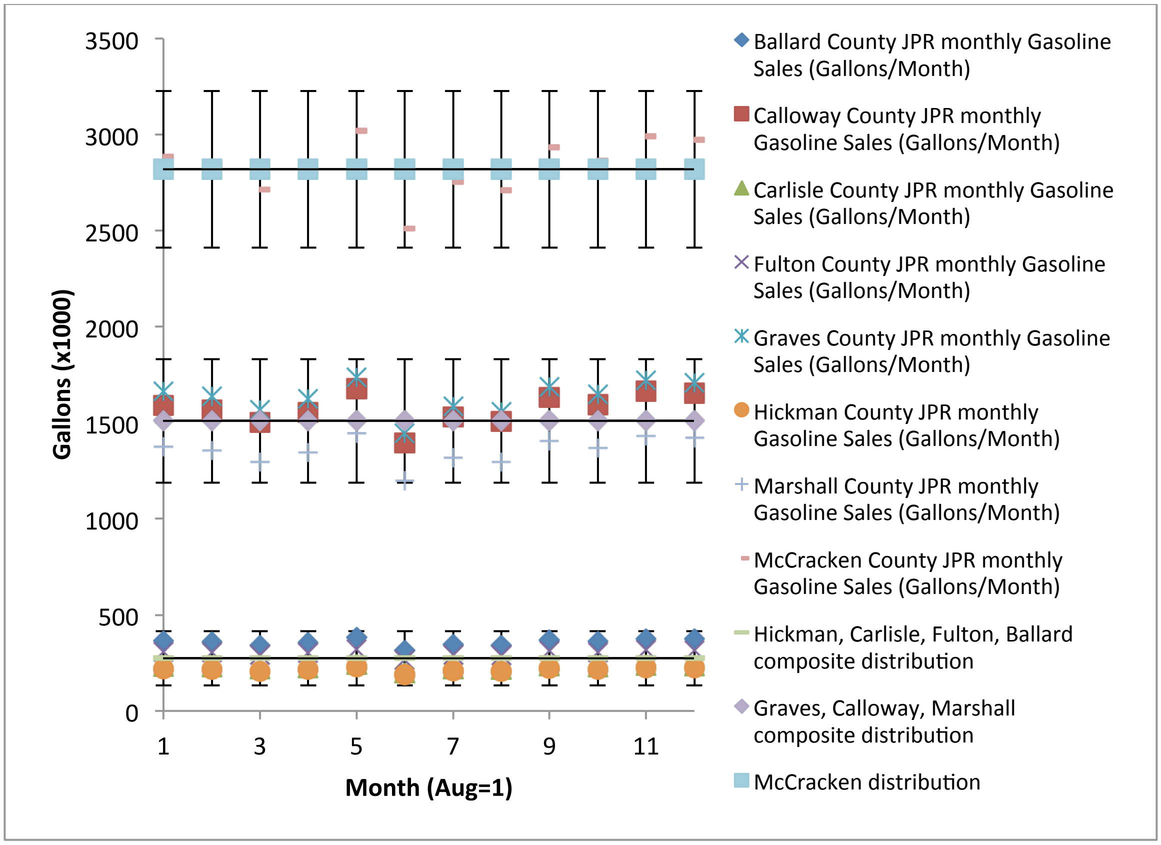


Figure 5-21 Gasoline Demand Distribution Expected Values & Historic Means

5.4.2 Diesel Fuel Demand Generation

Special fuel sales in the state of Kentucky represent a combination of fuel alternatives to gasoline including diesel fuel. It is assumed that these sales represent primarily the sale of diesel fuel and that other alternative fuel sales are negligible. Therefore, special fuel sales allow for a measure of diesel demand. These data were collected for the time period including August 2004 to July 2011 (US DOT, 2011) and converted to county level data, similarly to the gasoline data, according to the method described by Faulkner (2012). The averages of the resulting data set can be seen in Table 5-14.

Table 5-14 Average JPR special fuel consumption – [Gallons x 1,000,000]

County	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Ballard	0.12	0.13	0.14	0.13	0.12	0.15	0.13	0.14	0.15	0.14	0.14	0.13
Calloway	0.52	0.59	0.61	0.59	0.55	0.65	0.56	0.59	0.64	0.59	0.60	0.57
Carlisle	0.08	0.09	0.09	0.08	0.08	0.09	0.08	0.09	0.09	0.09	0.09	0.08
Fulton	0.10	0.11	0.12	0.11	0.10	0.12	0.11	0.12	0.12	0.12	0.12	0.11
Graves	0.54	0.61	0.63	0.61	0.57	0.67	0.58	0.62	0.67	0.62	0.63	0.59
Hickman	0.07	0.08	0.08	0.08	0.07	0.09	0.08	0.08	0.09	0.08	0.08	0.08
Marshall	0.45	0.51	0.53	0.51	0.47	0.56	0.49	0.51	0.55	0.51	0.52	0.49
McCracken	0.94	1.07	1.10	1.06	0.98	1.17	1.01	1.08	1.16	1.08	1.09	1.03

Similarly to the gasoline sales data, counties with similar consumption were grouped, their data points were aggregated, and combined distribution functions were determined using ARENA Input Analyzer. The generated distributions are shown in Table 5-15.

Table 5-15 Diesel Fuel Demand Distributions

Month	County	Distribution
January - December	Ballard	61700+ERLA(2.01e+004,2)
	Calloway	NORM(5.65e+005,7.36e+004)
	Carlisle	61700+ERLA(2.01e+004,2)
	Fulton	61700+ERLA(2.01e+004,2)
	Graves	NORM(5.65e+005,7.36e+004)
	Hickman	61700+ERLA(2.01e+004,2)
	Marshall	NORM(5.65e+005,7.36e+004)
	McCracken	NORM(1.05e+006, 1.08e+005)

Distribution performance relative to historic means can be seen in Figure 5-22.

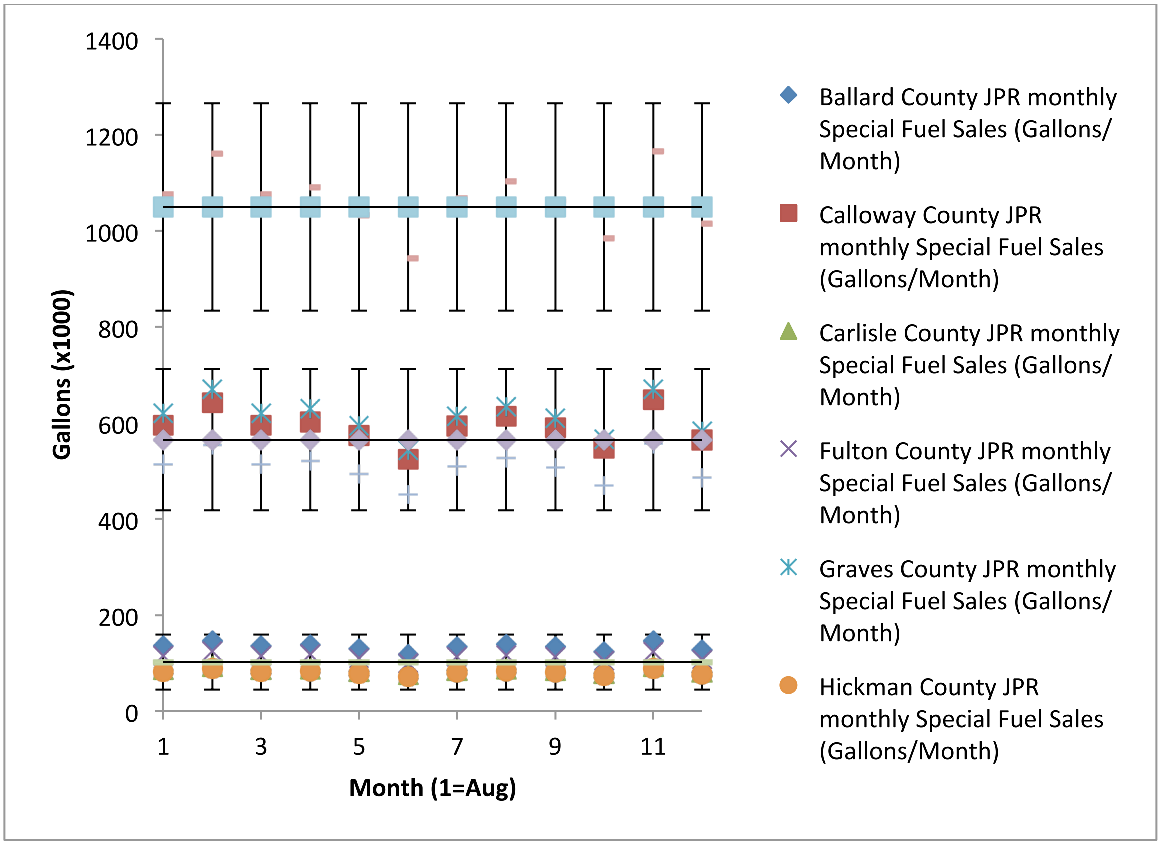


Figure 5-22 Diesel Fuel Demand Distribution Expected Values & Historic Means

5.4.3 Electricity Demand Generation

Similarly to Faulkner (2012), for the purposes of modeling the regional generation of electricity is used as a measure of electricity demand. Energy export via transmission lines is not taken into consideration. The average JPR county level data are displayed in Table 5-16.

Table 5-16 Average JPR electricity generation – [MWh x 100,000]

County	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Ballard	0.16	0.17	0.15	0.14	0.14	0.17	0.17	0.17	0.16	0.14	0.15	0.16
Calloway	0.69	0.75	0.65	0.60	0.60	0.73	0.74	0.73	0.69	0.61	0.65	0.73
Carlisle	0.10	0.11	0.09	0.09	0.09	0.10	0.11	0.11	0.10	0.09	0.09	0.10
Fulton	0.13	0.14	0.12	0.12	0.11	0.14	0.14	0.14	0.13	0.12	0.13	0.14
Graves	0.71	0.78	0.67	0.62	0.62	0.76	0.77	0.76	0.72	0.64	0.68	0.75
Hickman	0.09	0.10	0.09	0.08	0.08	0.10	0.10	0.10	0.10	0.08	0.09	0.10
Marshall	0.59	0.65	0.56	0.52	0.52	0.63	0.64	0.63	0.60	0.53	0.56	0.63
McCracken	1.24	1.35	1.17	1.09	1.08	1.31	1.34	1.32	1.25	1.11	1.18	1.31

These average values are computed from state level monthly electricity data that has been collected from the Energy Information Agency (US EIA, 2012b) and converted to county level JPR data via the method described by Faulkner (2012). Again, similarly consuming counties have been grouped and aggregate distributions have been generated from the combined data sets using ARENA Input Analyzer. The generated distributions can be seen in Table 5-17.

Table 5-17 Electricity Demand Distributions

Month	County	Distribution
January - December	Ballard	7.6e+003 + 1.12e+004 * BETA(1.08, 1.71)
	Calloway	TRIA(4.89e+004, 6.47e+004, 8.47e+004)
	Carlisle	7.6e+003 + 1.12e+004 * BETA(1.08, 1.71)
	Fulton	7.6e+003 + 1.12e+004 * BETA(1.08, 1.71)
	Graves	TRIA(4.89e+004, 6.47e+004, 8.47e+004)
	Hickman	7.6e+003 + 1.12e+004 * BETA(1.08, 1.71)
	Marshall	TRIA(4.89e+004, 6.47e+004, 8.47e+004)
	McCracken	1.03e+005 + 4.67e+004 * BETA(1.24, 1.56)

The relative performance of each generated distribution compared to historic mean values of electricity production can be seen in Figure 5-23.

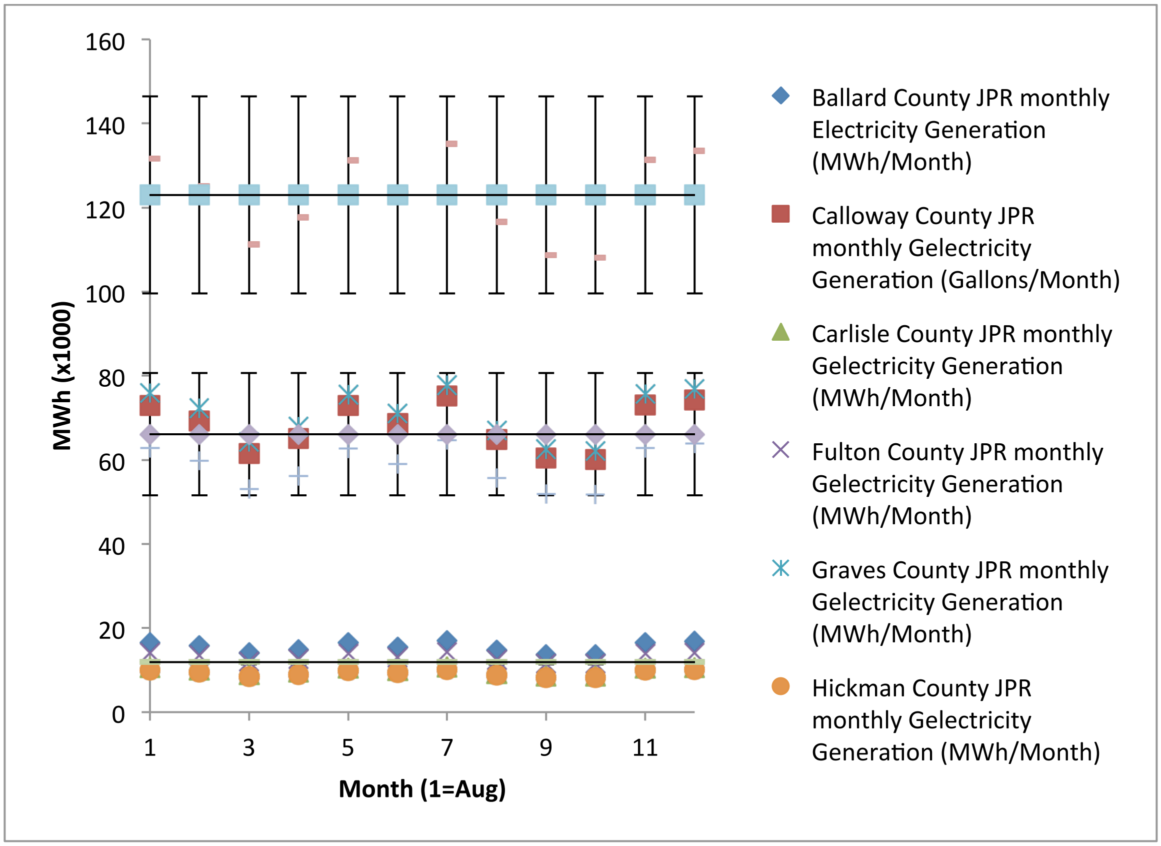


Figure 5-23 Electricity Demand Distribution Expected Values & Historic Means

5.4.4 Natural Gas Demand Generation

Natural gas consumption has been quantified as the volume of total natural gas delivered for all purposes on the state level on a monthly basis (US EIA, 2012c). The method for converting this data to JPR county level data described by Faulkner (2012) is again followed and the average values for each month and each county can be seen in Table 5-18.

Table 5-18 Average JPR delivered natural gas – [Mcf x 100,000]

County	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Ballard	0.50	0.54	0.39	0.29	0.22	0.23	0.22	0.24	0.22	0.25	0.36	0.50
Calloway	2.23	2.41	1.72	1.28	0.98	1.02	0.99	1.07	0.97	1.12	1.57	2.21
Carlisle	0.32	0.34	0.25	0.18	0.14	0.15	0.14	0.16	0.14	0.16	0.23	0.32
Fulton	0.42	0.46	0.33	0.24	0.19	0.20	0.19	0.21	0.19	0.22	0.31	0.42
Graves	2.30	2.49	1.78	1.32	1.02	1.06	1.02	1.12	1.02	1.17	1.64	2.28
Hickman	0.30	0.33	0.23	0.17	0.13	0.14	0.13	0.15	0.13	0.15	0.22	0.30
Marshall	1.91	2.07	1.48	1.10	0.84	0.88	0.85	0.92	0.84	0.96	1.36	1.90
McCracken	4.00	4.32	3.10	2.30	1.77	1.84	1.77	1.93	1.76	2.02	2.84	3.97

As with the other biorefinery products, counties with similar levels of consumption have been grouped together. Unlike the other products, however, the consumption of natural gas displays nonlinearity forming a peak during the year. This can be attributed to the significant increase in use of the fuel for heating businesses and homes during winter months. To account for this difference, multiple distributions for each group of counties were generated with ARENA Input Analyzer to correspond with different levels of consumption in a particular month. The resulting generated distribution functions are displayed in Table 5-19.

Table 5-19 Natural Gas Demand Distributions

Month	County	Distribution
October - March	Ballard	TRIA(1.01e+004, 1.45e+004, 3.09e+004)
	Calloway	NORM(9.93e+004, 1.4e+004)
	Carlisle	TRIA(1.01e+004, 1.45e+004, 3.09e+004)
	Fulton	TRIA(1.01e+004, 1.45e+004, 3.09e+004)
	Graves	NORM(9.93e+004, 1.4e+004)
	Hickman	TRIA(1.01e+004, 1.45e+004, 3.09e+004)
	Marshall	NORM(9.93e+004, 1.4e+004)
	McCracken	NORM(1.85e+005, 2.13e+004)
April, August - September	Ballard	TRIA(1.33e+004, 1.92e+004, 4.69e+004)
	Calloway	NORM(1.46e+005, 2.58e+004)
	Carlisle	TRIA(1.33e+004, 1.92e+004, 4.69e+004)
	Fulton	TRIA(1.33e+004, 1.92e+004, 4.69e+004)
	Graves	NORM(1.46e+005, 2.58e+004)
	Hickman	TRIA(1.33e+004, 1.92e+004, 4.69e+004)
	Marshall	NORM(1.46e+005, 2.58e+004)
	McCracken	NORM(2.73e+005, 4.3e+004)
May - July	Ballard	TRIA(2.45e+004, 3.1e+004, 6.34e+004)
	Calloway	NORM(2.22e+005, 2.91e+004)
	Carlisle	TRIA(2.45e+004, 3.1e+004, 6.34e+004)
	Fulton	TRIA(2.45e+004, 3.1e+004, 6.34e+004)
	Graves	NORM(2.22e+005, 2.91e+004)
	Hickman	TRIA(2.45e+004, 3.1e+004, 6.34e+004)
	Marshall	NORM(2.22e+005, 2.91e+004)
	McCracken	NORM(4.14e+005, 4.28e+004)

The expected value of each distribution function has been compared to the historic mean. The results are shown in Figure 5-24; the historic means all fall within one standard deviation of the distribution function expected value.

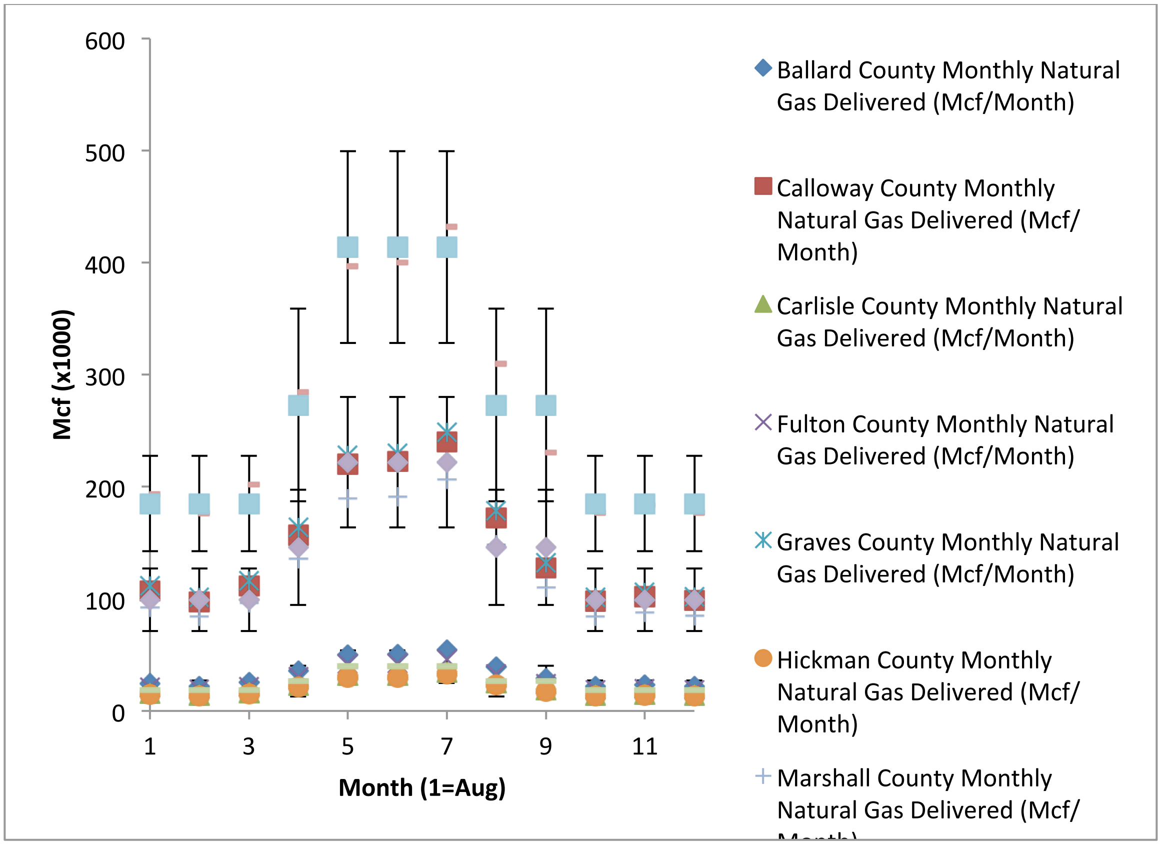


Figure 5-24 Natural Gas Demand Distribution Expected Values & Historic Means

5.4.5 Residual Fuel Oil

Unlike the other products discussed, residual fuel oil is not a consumer product. Therefore, allocating the demand to the county level based on populations via the methodology described by Faulkner (2012) is not applicable. This fact, coupled with a lack of available county level data for residual fuel oil consumption, leads to difficulty in defining consumption on the county level. The fact that residual fuel oil is used at the defined terminal locations as bunker fuel oils for river transportation, as well as having other various uses, justifies an assumption that all produced residual fuel oil will be sold. Demand distributions were not created for this product.

6 RESULTS & ANALYSIS

6.1 Biorefinery Supply Chain Simulation Model

After chemical process optimization and supply chain optimization had been carried out and the appropriate inputs from the respective models were obtained, the methodology for supply chain modeling with discrete event simulation was carried out. A major output of this exercise is the simulation model itself. Care was taken to ensure that assumptions among the three component models were consistent, as previously described. Evaluation of the selected optimal supply chain was carried out utilizing the model adapted to these inputs. The model view screen shot with different sections labeled is shown in Figure 6-1. Each subsection noted in the figure carries out specific tasks described in detail in Chapter 4 (Methodology). Subsequent discussion will illuminate the model in more detail.

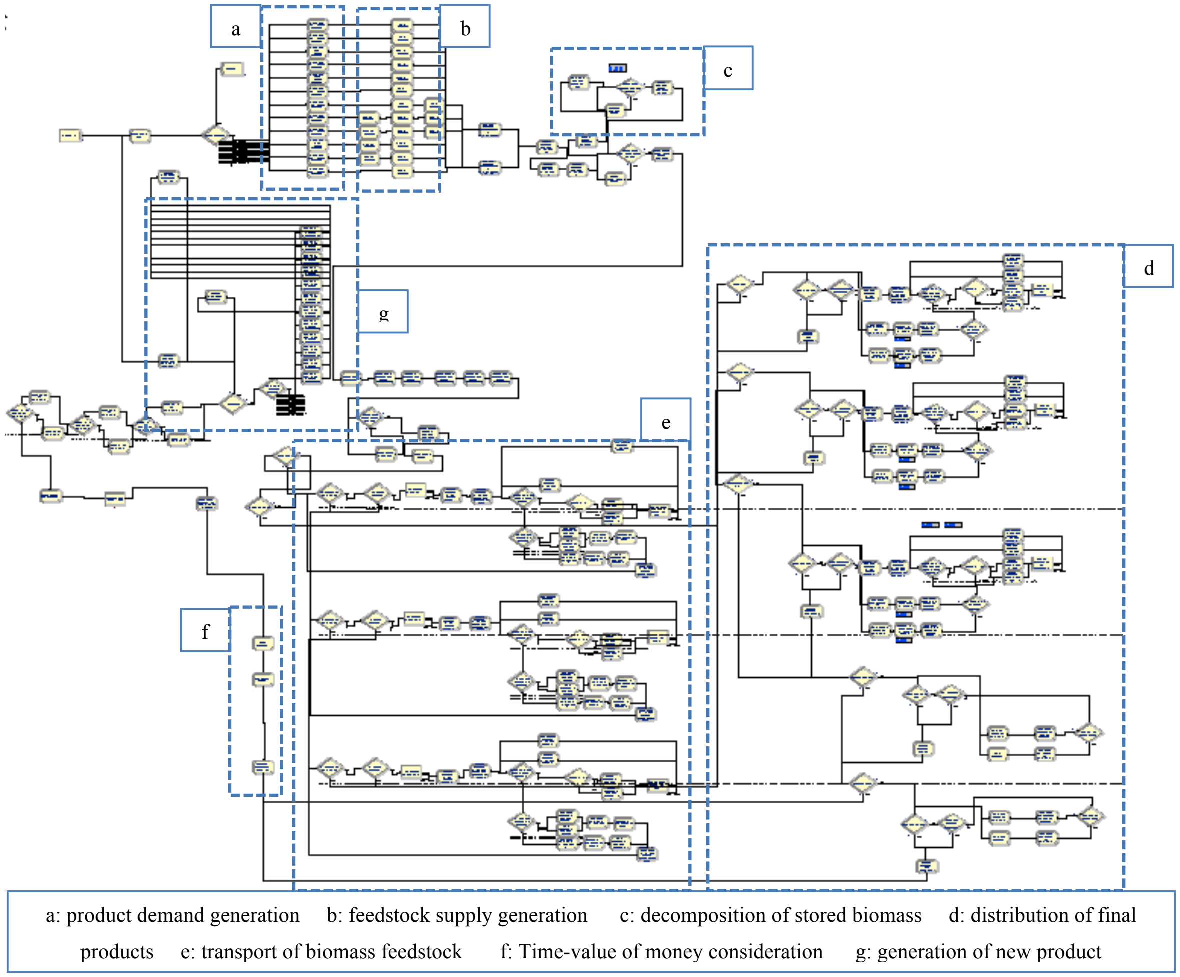


Figure 6-1 multi-feedstock biorefinery supply chain discrete event simulation model

This model was run for a period of 10 years in order to examine the long term profitability of the system taking into consideration capital cost, transportation costs, diesel fuel expenses, storage costs, operating costs, and raw material costs paid for the feedstocks. The following sections will describe the findings from this modeling.

Figure 6-1 section a and b have been expanded in Figure 6-2. A control entity enters the figure from the left-hand side, following the path specific to the current month in simulation time. Product demand and new feedstock supply for the day are generated using distribution functions described in Chapter 5. Biorefinery requirements for each biomass are checked for changes (a feature included for future expansions of the model:

currently, this parameter is a deterministic value provided from process modeling) and biomass storage arrays are updated to track the stock of biomass available for shipment.

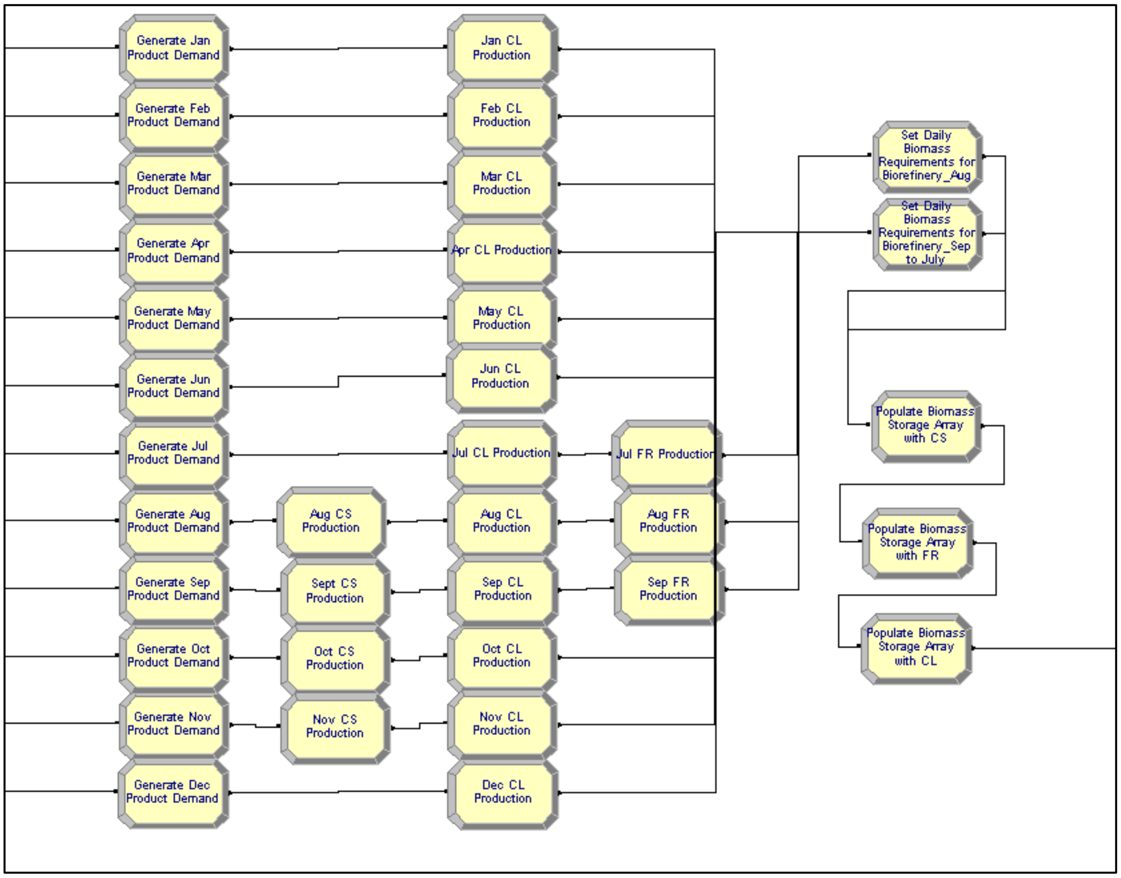


Figure 6-2 Product Demand (a) and Feedstock Supply Generation (b)

Figure 6-1 section c is magnified in Figure 6-3. Here, stored biomass in the system is allowed to decay via the deterministic rate identified previously (DR).

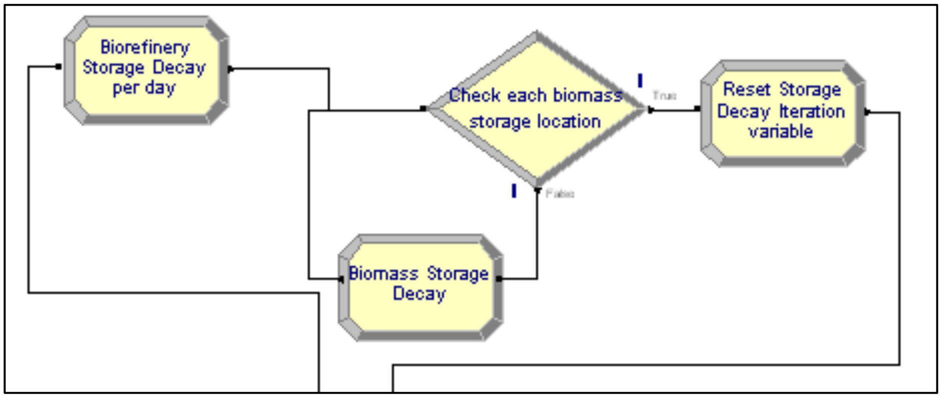


Figure 6-3 Stored Feedstock Decomposition (c)

Figure 6-4 and 6-5 detail the modeling typical of Figure 6-1 section d. Figure 6-4 is the module utilized to simulate the distribution of liquid fuel products. The stock of a particular product at the biorefinery is checked. If supply is present, demand for the corresponding product is assessed. Subsequently, logic selects the nearest (i.e. optimal) demand location via the methodology described in Chapter 4. The variables associated with product supply are adjusted to capture the sale of the product and, finally, income from the day's sale of the product is recorded.

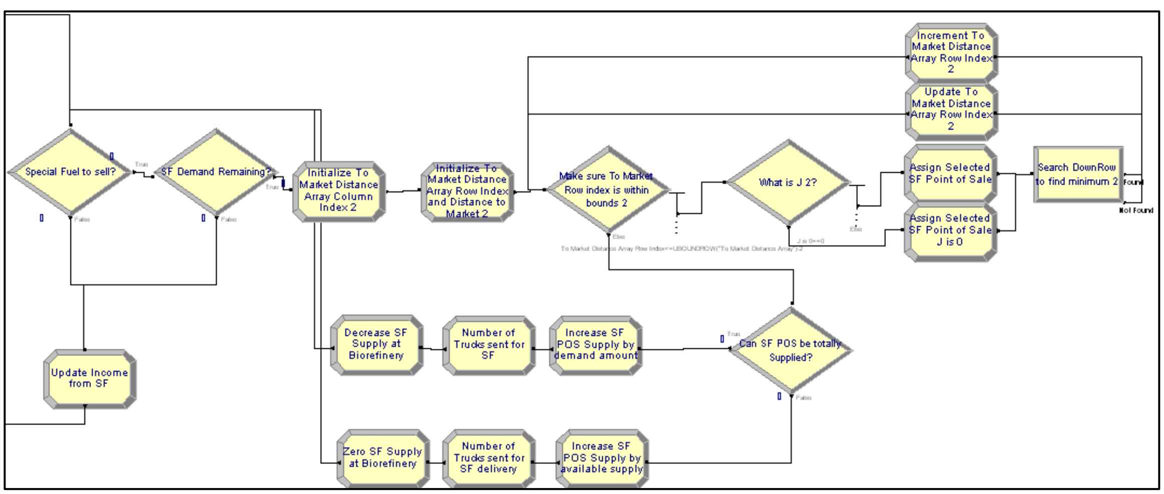


Figure 6-4 Distribution of Final Products – Type 1 (d)

As has been mentioned, the distribution of other products, such as natural gas and electricity for this case study, did not require transportation due to assumed integration with existing delivery infrastructure. This results in a much simpler distribution simulation. As an example, Figure 6-5 outlines the simulation of the distribution of natural gas. Similar to liquid fuels, supply and demand are checked, distribution occurs, and income is recorded. Instead of seeking the optimal supply location, the natural gas supply diminishes the network's aggregated demand; similar considerations are taken in the case of electricity distribution.

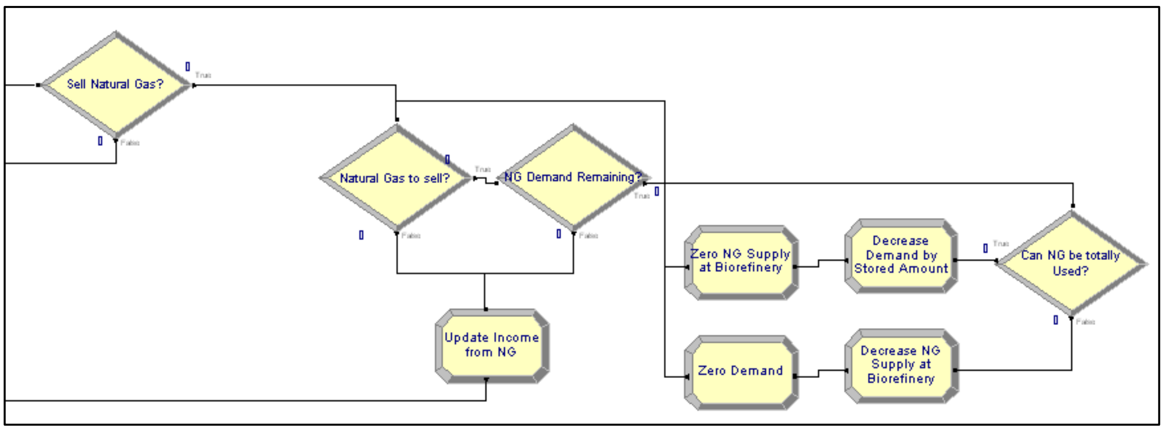


Figure 6-5 Distribution of Final Products – Type 2 (d)

Figure 6-6 highlights an example of biomass supply transportation found in Figure 6-1 section e. The supply of a particular biomass relative to the biorefinery requirements for a given day is assessed. If additional feedstock is needed at the biorefinery, supply availability is checked; given biorefinery need and any available supply, the logic described in Chapter 4 selects the optimal (nearest) supply location with availability. Storage variables are updated to reflect the delivery of material. Costs associate with the purchase of a particular feedstock and its transportation are assessed at this time.

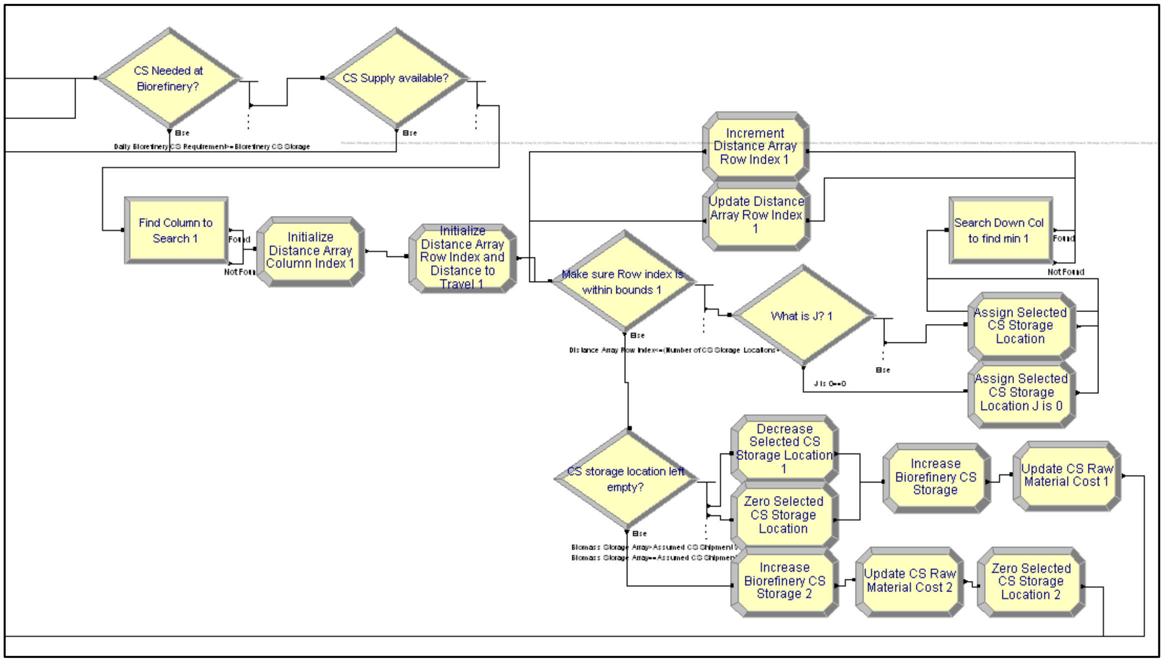


Figure 6-6 Transportation of Biomass Feedstock (e)

Cost aggregation, application of the discounted cash flow method for the calculation of net present value of investment, and the provision for the application of subsidies make up section f of Figure 6-1. These modules are displayed in Figure 6-7. The costs associate with feedstock acquisition, transportation activities, biorefinery operation, and production of products are aggregated and subtracted from the income on a daily basis. These values are discounted with an assumed interest rate (r) to give units of current dollars. The discounted cash flow method procedure applied is discussed in section 6.1. A module for the inclusion of subsidies in analysis, which effectively increases the discounted income of the biorefinery, is found in this portion of the ARENA model as well.

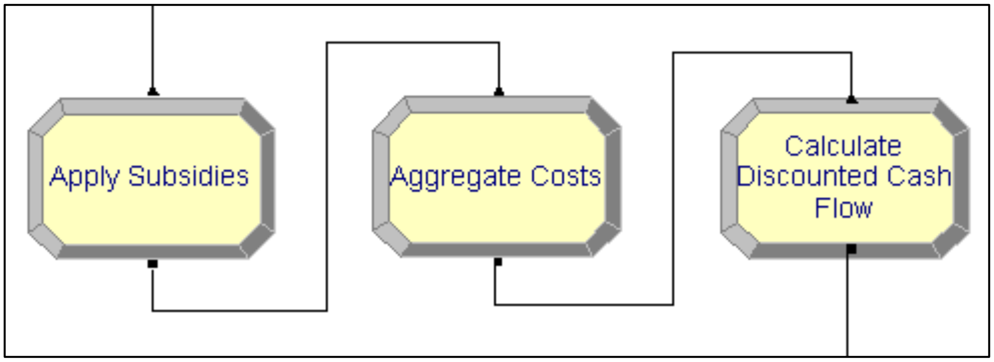


Figure 6-7 Time Value of Money Consideration (f)

Finally, Figure 6-8 highlights the portion of the modeling (Figure 6-1 section g) responsible for simulating the production of products from feedstock at the biorefinery. Here, feedstock present at the biorefinery is multiplied by a conversion factor determined from the information provided by process simulation (see Table 5-1) yielding the volumes of product for distribution and sale on the next day in simulation. Operating costs for the simulated day is applied according the month and the appropriate associated deterministic operating cost parameter (DOC_A or $DOC_{S\text{-}J}$, depending on the month). Storage costs are assessed to be aggregated in the next simulated day based on the biomass remaining in storage and the deterministic parameter associated with storage costs per ton (SC).

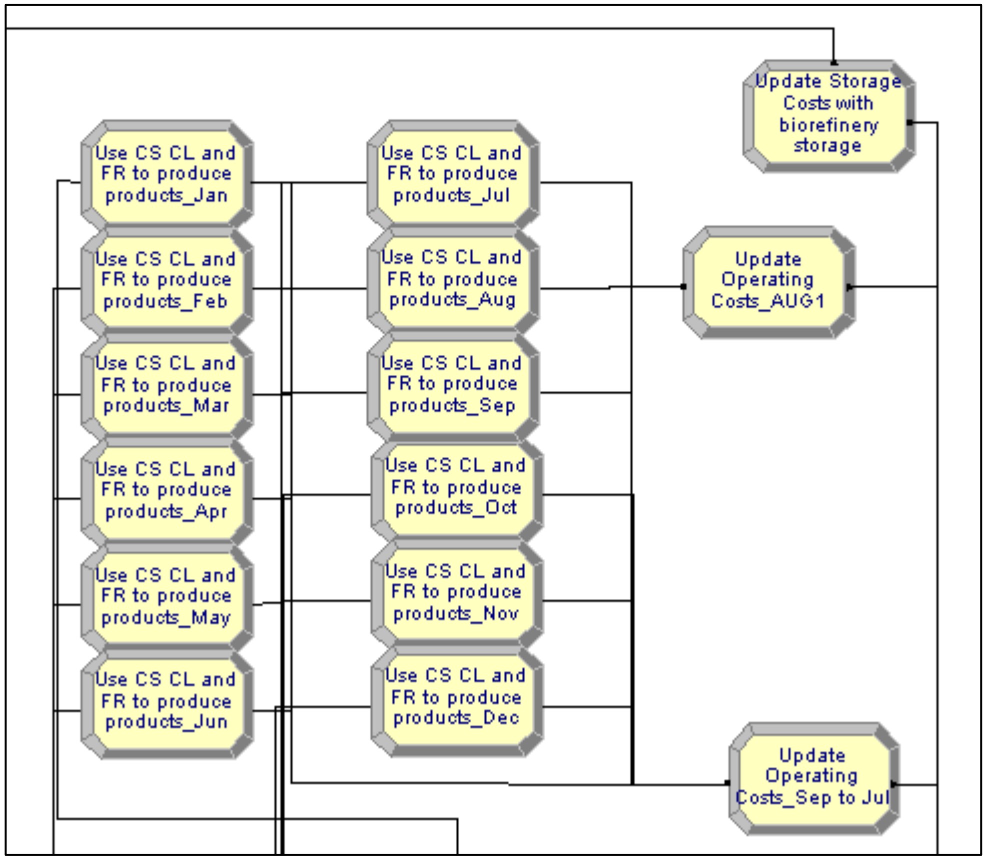


Figure 6-8 Generation of New Product (g)

Other ARENA modules seen in Figure 6-1 were omitted from discussion due to the nature of their functions. These modules perform various bookkeeping activities, make it possible to examine individual portions of the model, and reset variables after a system cycle has been completed, for example.

6.2 Supply Chain Performance Report

The supply chain activities for the described case study were simulated over a period of 10 years. Costs associated with each transportation, sale, and production aspect of the chain were tracked to evaluate the overall, long term profitability and economic sustainability of the biorefinery supply chain. A primary goal of this simulation modeling exercise was to learn the characteristics of this type of supply chain and, ultimately draw generalized conclusions from the study. To that end, transportation costs for biomass and biorefinery products, raw material costs, transportation and fuel costs, operating costs, and storage costs were aggregated for each day of operation. Additionally, income derived from the sale of products in the marketplace was recorded in order to examine the revenues created by the supply chain system. Overall plant capital cost was also taken into consideration for potential evaluations of a biorefinery payback period.

Since this study is covers an extended period, it was necessary to include consideration of the time-value of money in these analyses. This was accomplished through the calculation of the Net Present Value (NPV) of the continuing investment in biorefinery supply chain activities via the discounted cash flow method. This method discounts revenues from a given operation to present dollar values utilizing Equation 6-1 where DPV is the discounted present value of all future values (FV_t) of positive and negative cash flows for a given time period, N. In this equation, the value of the variable *r* is an assumed constant value of the interest rate. For modeling purposes this value is assumed to be 3% per year.

$$DPV = \sum_{t=0}^{N} \frac{FV_t}{(1+r)^t} \tag{6-1}$$

For the small biorefinery, the discounted cash flow method was applied to the optimal supply chain configuration determined by Faulkner (2012) for the small integrated biorefinery in the Jackson Purchase Region. These values are plotted in Figure 6-9 for the entire ten year duration of the simulation run. The values plotted represent the average values obtained from five iterations of the simulation model. Figure 6-9 displays the values of NPV for the biorefinery investment as a function of simulation time.

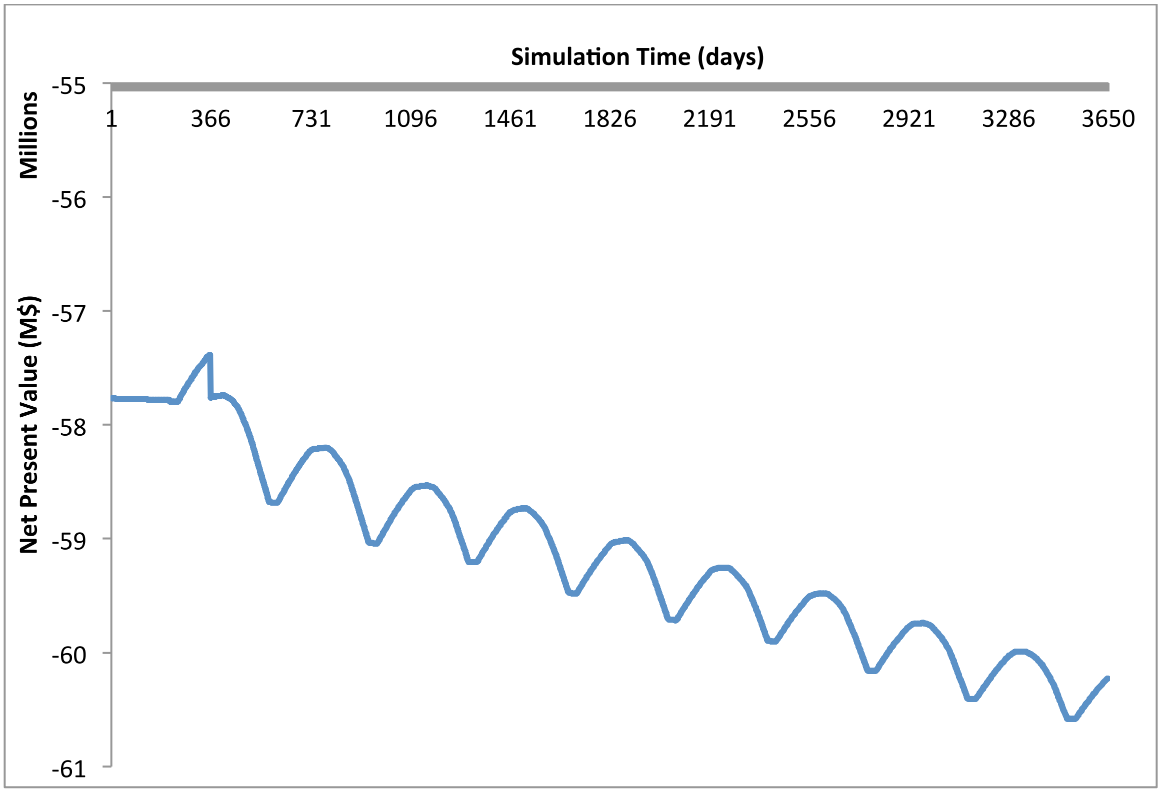


Figure 6-9 NPV Variations – Small Biorefinery Supply Chain

From the plot of daily values of NPV in Figure 6-2 it is clear that the supply chain will never yield a profit. Given an initial investment (determined by process optimization modeling) annual losses ensure that the cumulative NPV shows a continuous decline. There are, however, certain portions of the curve with a positive trajectory. It is important to examine this phenomenon in order to identify aspects of the supply chain design that may be leveraged to improve overall net present value of the system. The average daily revenues (total income — aggregated costs) across 5 simulation replications for the biorefinery are plotted in Figure 6-10.

The magnitudes of cyclical variations in revenues shed light on the negatively trending NPV seen in Figure 6-9. As there are only short periods over which revenue is generated and the magnitude of this positive cash flow is small compared to negative cash flows, it is inevitable that the NPV of the overall investment will decline in the long run.

Since the negative portions of the revenue plot are significantly larger in magnitude than the positive portions, it is inevitable that investment present value will steadily decline in the long term.

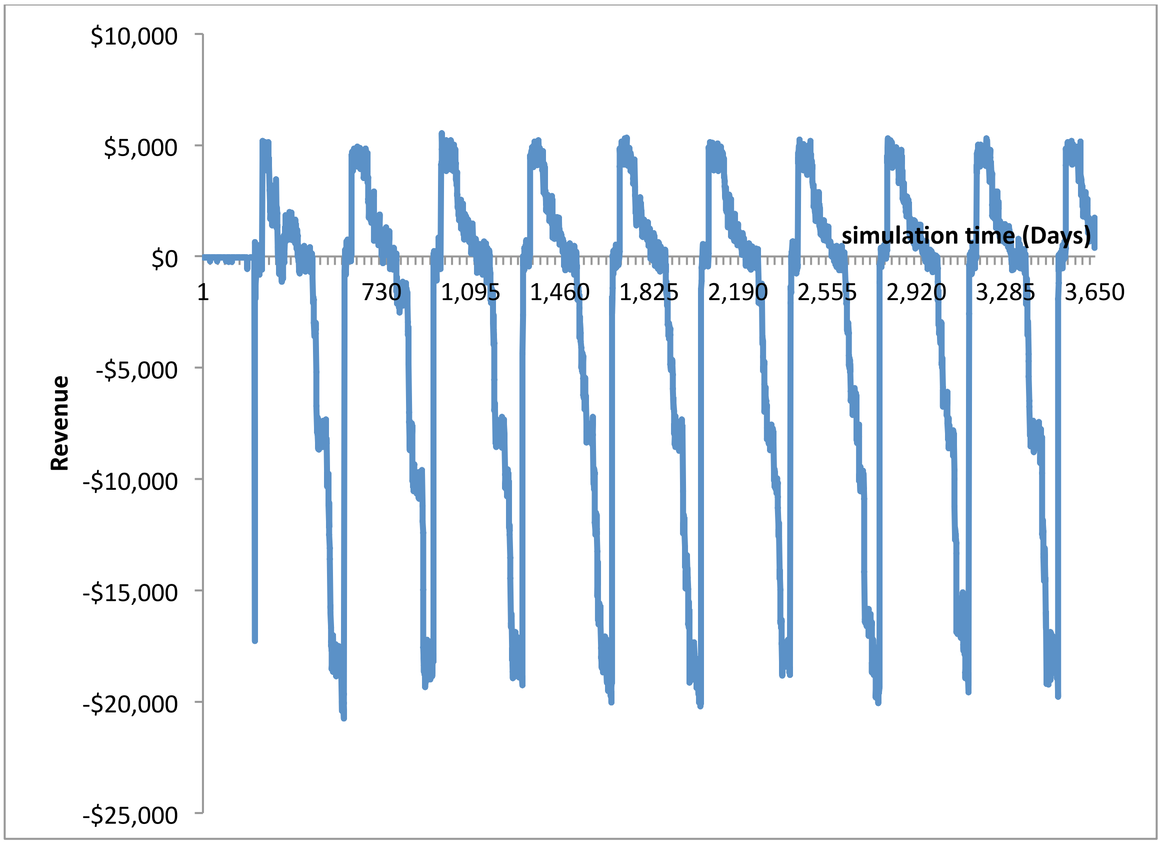


Figure 6-10 Daily Revenue Variation – Small Biorefinery Supply Chain

To further investigate this seasonal pattern that has emerged in Figure 6-10, it is helpful to select a representative year among those modeled and assess their average monthly revenues. By doing this, insight can be gained regarding which months are profitable for the supply chain in question. This analysis has been done and can be seen as Figure 6-11. It can be seen that the supply chain realizes an operating profit during the months associated with the corn stover harvest season. Although the supply chain modeled is multi-feedstock, the daily biorefinery requirements are dominated by corn stover. This dependence on that resource is clearly reflected in the plot seen in Figure 6-11.

It should be noted that the plot of average revenues for each month closely mirrors the results obtained by Faulkner (2012) indicating that the supply chain being modeled is, in fact, the optimal solution to the location allocation problem. Comparison of this plot and the Faulkner results clearly highlight the value of simulation modeling in addition to linear optimization. These implications are discussed in future chapters; however, it seems evident that projection of the investment into the future gives a much clearer picture of the reality that this supply chain configuration, although optimal, will likely never reach profitability.

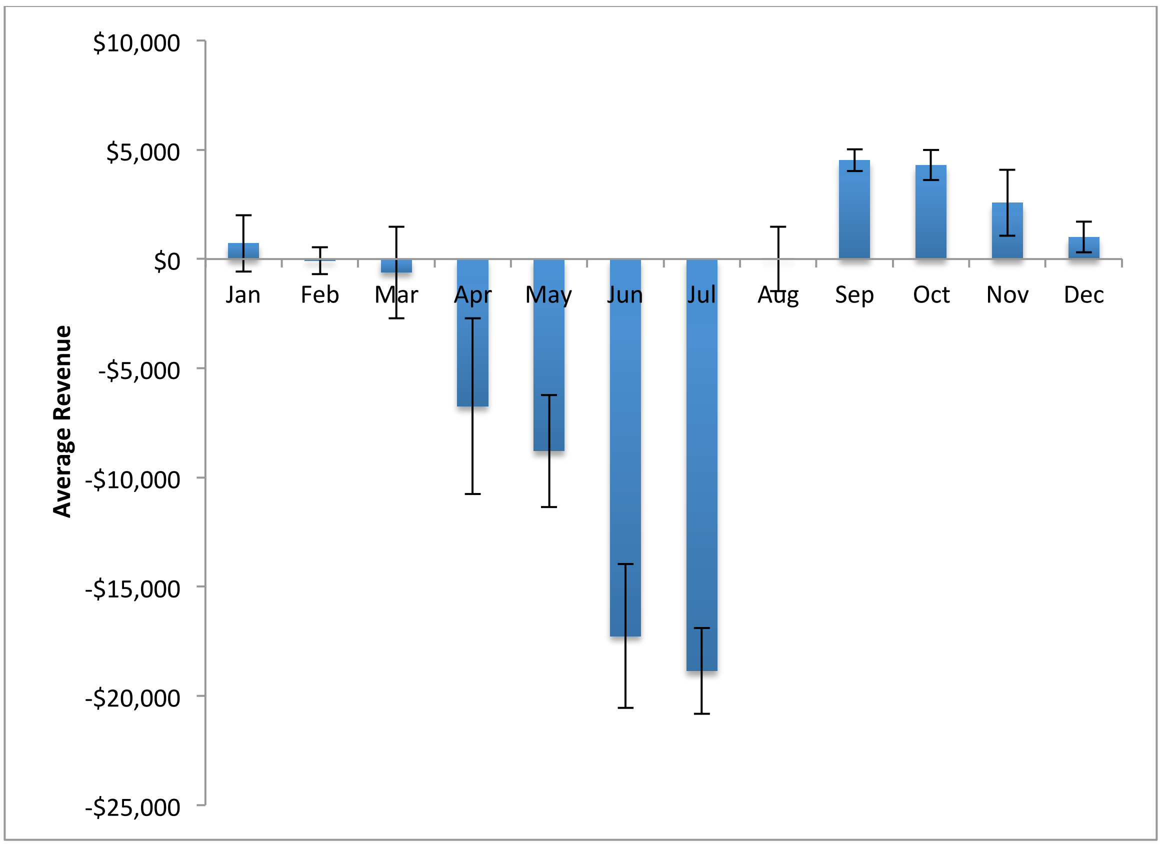


Figure 6-11 Sample Average Monthly Revenues – Small Biorefinery

For similar analysis, the net present value for the medium size biorefinery is shown in Figure 6-12. Unlike the small biorefinery supply chain this NPV shows positive trajectory. However, the investment does not break even during the simulation time horizon of ten years. Applying a linear regression model to the data and extrapolating, allows the determination of an approximate payback period for the biorefinery investment. The regression model is shown in Equation 6-2.

$$NPV = 11542\,\mathrm{t} - 60000000; \qquad R^2 = 0.9956 \tag{6-2}$$

In this way, a payback period of 14.24 years is determined. It is important, however, to caution that this payback period represents an optimistic viewpoint and illustrates the impact that assumption selection can have on the outcome of modeling. Several costs, such as managerial costs, overhead costs, and maintenance costs would significantly alter this perspective by negatively shifting the NPV plot vertically. The result of any negative shift would be a prolonged payback period.

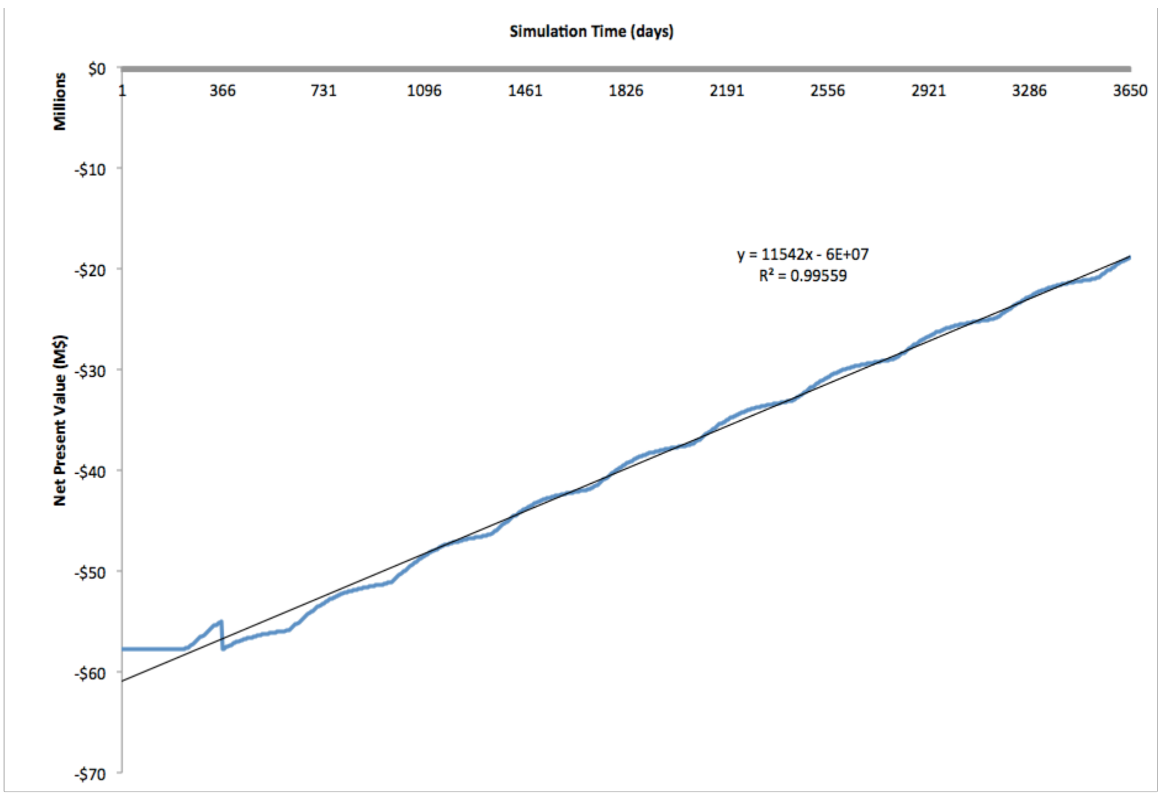


Figure 6-12 NPV Variation – Medium Biorefinery Supply Chain

In addition to the assumption considerations, the variance among the data increases with time as a reflection of the uncertainty associated with projecting costs and income into the future. This can be seen in the plot of standard deviation of the NPV as a function of time in Figure 6-13. These factors combine to limit the reliability of any prediction.

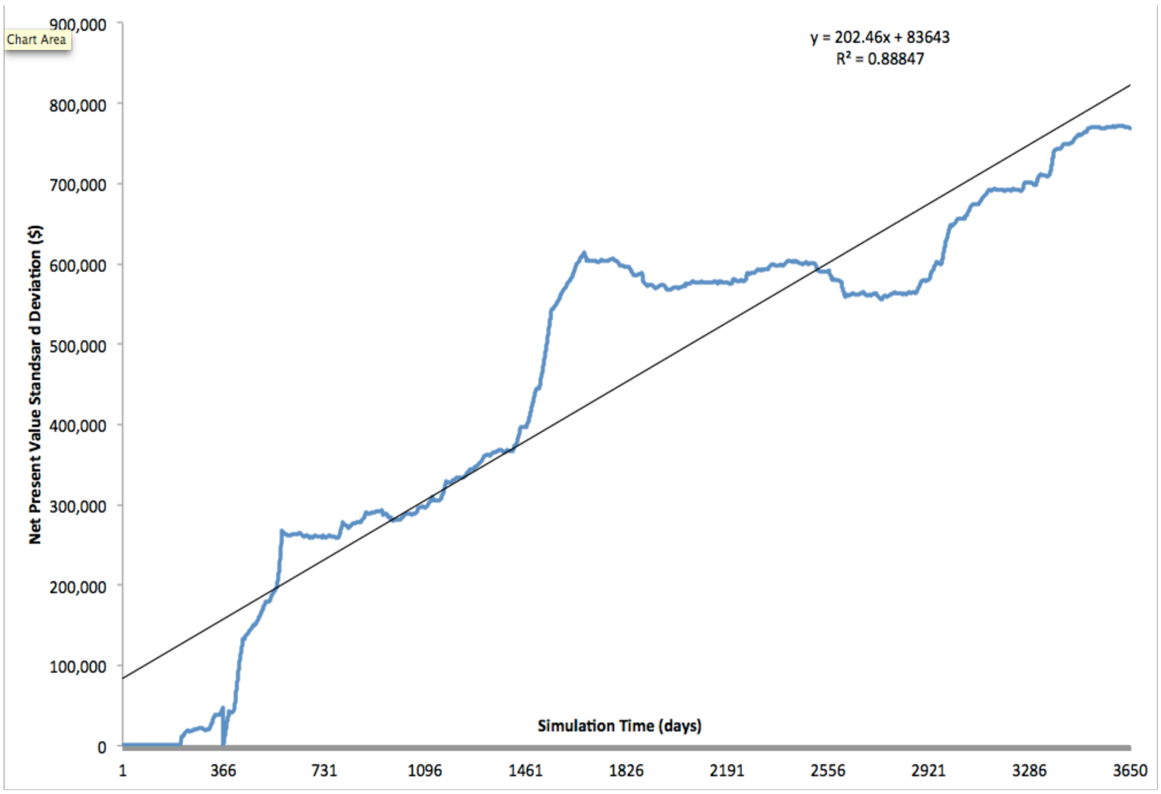


Figure 6-13 Standard Deviation of NPV – Medium Biorefinery

The daily revenues for the medium biorefinery are plotted in Figure 6-14. In this case, the daily revenues are positive in general. The monthly revenue trend is reflected in the average monthly revenues seen in Figure 6-15.

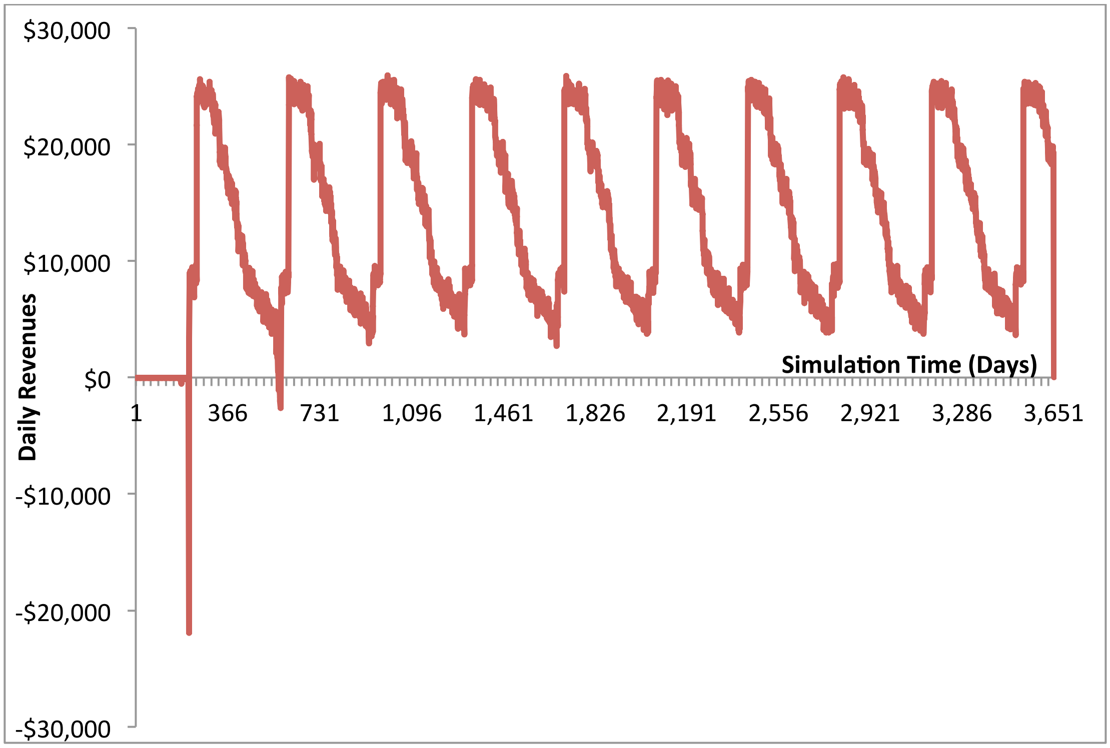


Figure 6-14 Daily Revenue Variation – Medium Biorefinery Supply Chain

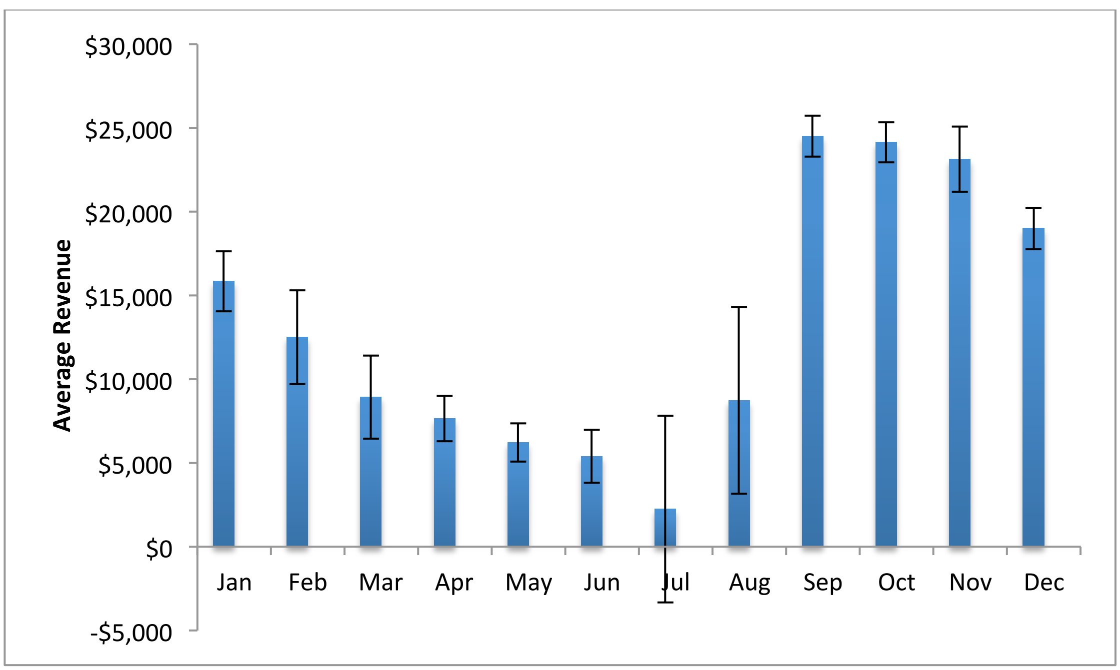


Figure 6-15 Sample Average Monthly Revenues – Medium Biorefinery

In this case, the income seen in the model outweighs the costs associated with the transportation of biomass; the biorefinery design successfully leverages its large production of residual fuel oils for increased profit. These results, it should be noted, do not directly match the results from Faulkner (2012) due to the model assumptions related to residual fuel oil sales. The simulation model assumes that residual fuel oil can be considered infinitely in demand due to its use as a bunker fuel at its sale location in McCracken County in the Jackson Purchase region, as suggested by Faulkner (2012). By deleting the income obtained directly from the sale of residual fuel oils, the negative profitability trend shown by Faulkner (2012) (and shown in Figure 3-4) is recreated. Deviation in the magnitude of the values seen can be attributed to the continued inclusion of costs related to residual fuel oil production and transportation that remain in the simulation results. The average monthly revenues without the inclusion of residual fuel oil income can be seen in Figure 6-16.

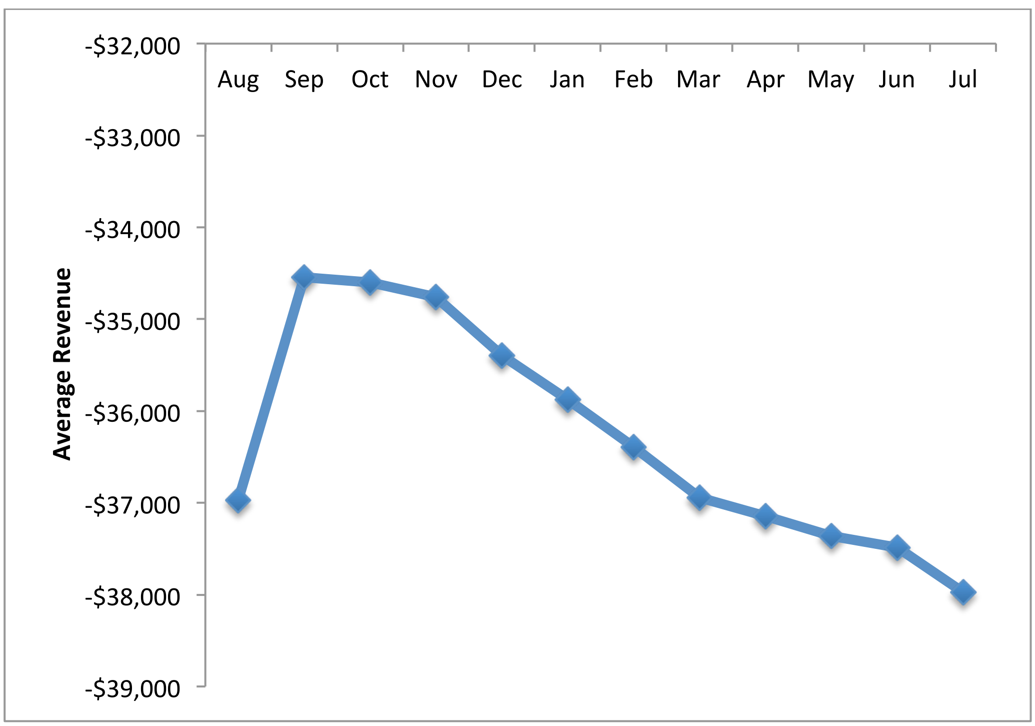


Figure 6-16 Sample Average Monthly Revenues without RFO – Medium Biorefinery

6.3 System Sensitivity Analysis

To understand the impact of several key assumptions made during modeling in simulation, as well as linear programming and process modeling, sensitivity analysis was a crucial activity. Using ARENA's Process Analyzer, control variables can be altered and responses in key performance indicators for the supply chain system can be examined. Primarily, analysis was carried out to examine the effect of varying some key assumed values in the simulation model.

Figure 6-17 shows the sensitivity of the investment net present value to varying prices for natural gas. The impact on net present value is captured via decreases in losses seen from investment in the Jackson Purchase Region small integrated biorefinery expressed in current dollars. In each of the sensitivity studies, a red data point indicates the currently assumed value from modeling.

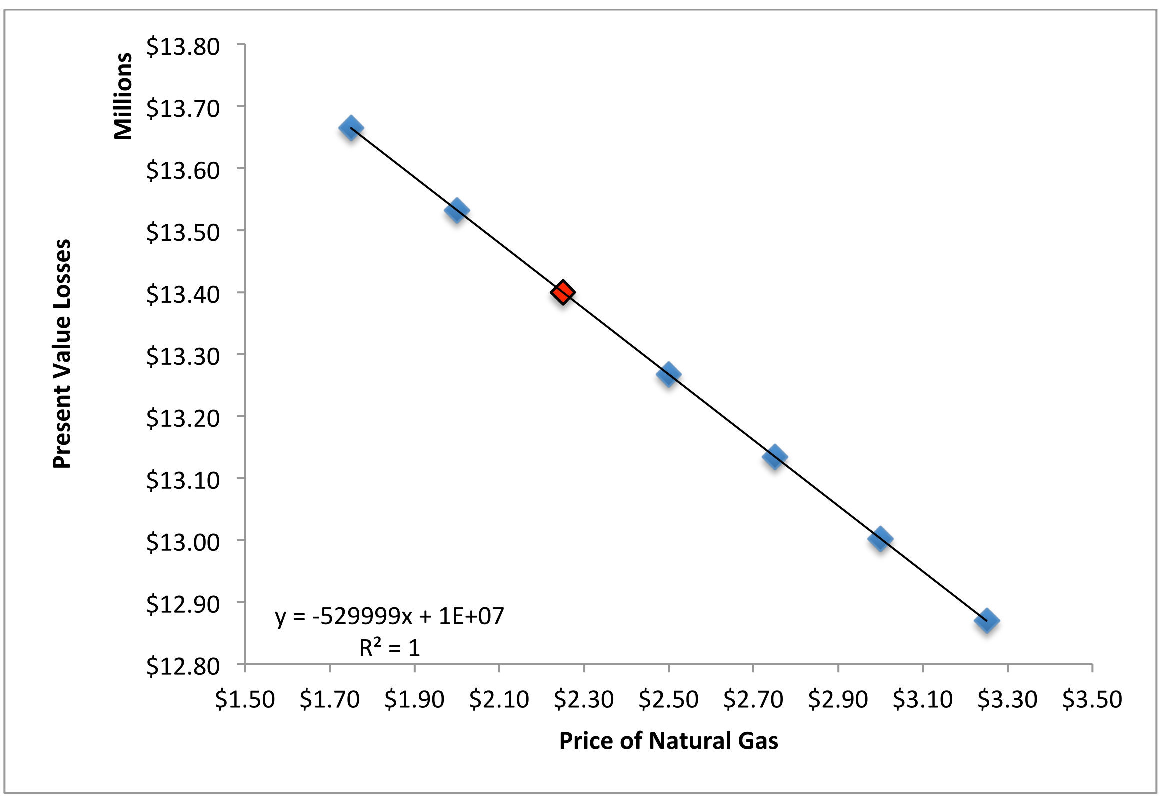


Figure 6-17 Sensitivity of Present Value losses to changes in natural gas price.

Similarly, the changes in present value loses observed with varying electricity price, residual fuel oil price, and gasoline price can be seen in Figures 6-18, 6-19, and 6-20, respectively. All of these products indicate a linear dependence of present value losses with the price of products sold by the biorefinery. This makes sense because increased prices for the commodities produced by the biorefinery supply chain will only increase income at the biorefinery. It should be noted, however, that effects such as changes in demand due to increasing cost have not been reflected in modeling. It is expected that as price of the product tends to infinity, the present value would settle to a limit governed by the relationship between the price of the good and demand for it. The only product sold that indicates the opposite trend is diesel fuel where, with increasing price, the net present value of the biorefinery supply chain decreases as seen in Figure 6-21. This can be attributed to the fact that diesel is consumed for the transportation of all products and feedstocks; the impact of increased diesel cost on transportation-related costs outweighs the increased revenue realized from the increased prices.

Linear regression models fit to these curves provide means to extrapolate and estimate conditions necessary for profitable supply chain results; in most cases, for the small biorefinery scenario, these conditions are relatively extreme. For instance, it is clear from Figure 6-12 that present value gains are not realized until gasoline prices reach between \$6.00 and \$6.50. It should be noted that with such large changes in product prices required for biorefinery profitability in this case, demand shifts are inevitable. Increased loses due to decreased income would be possibly significant enough to offset any gains from increased revenues realized due to higher prices.

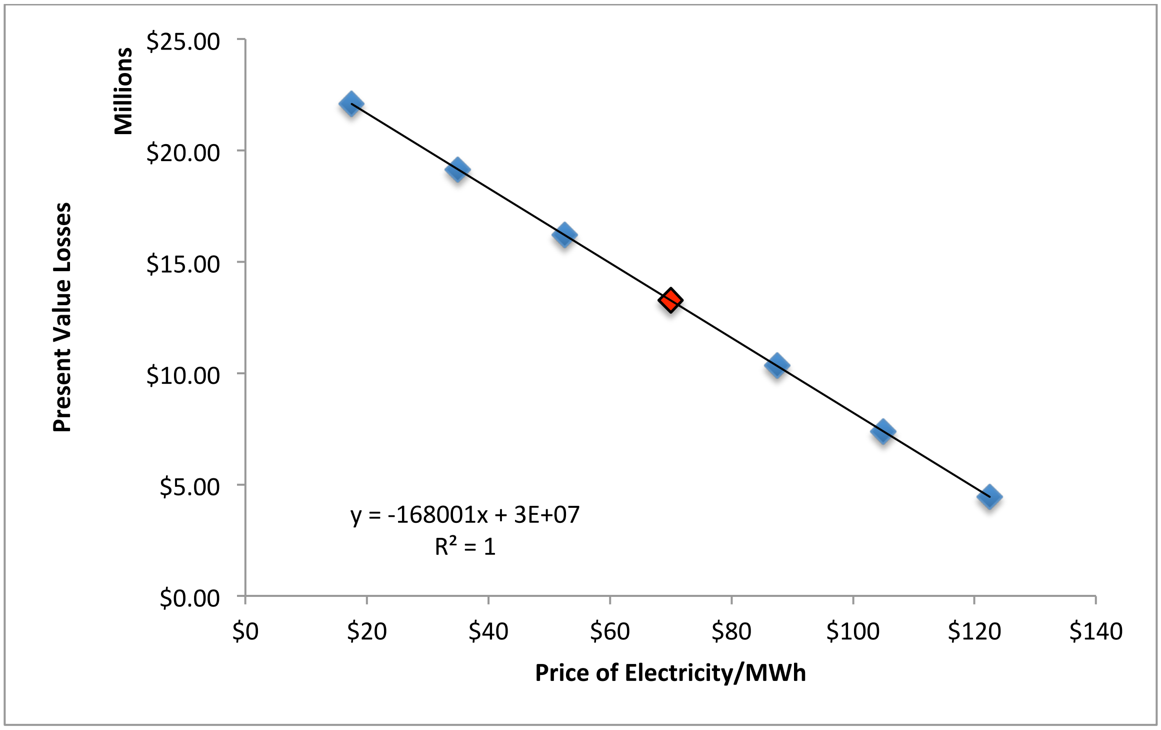


Figure 6-18 Sensitivity of Present Value losses to changes in electricity price.

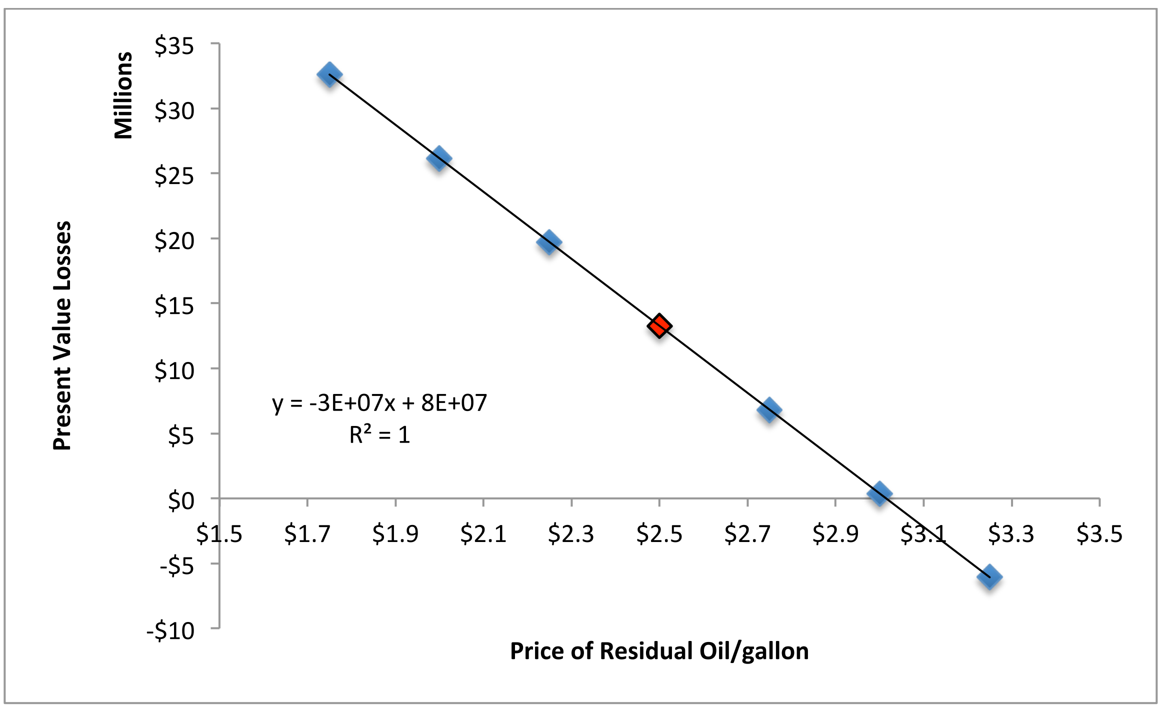


Figure 6-19 Sensitivity of Present Value losses to changes in residual fuel oil price.

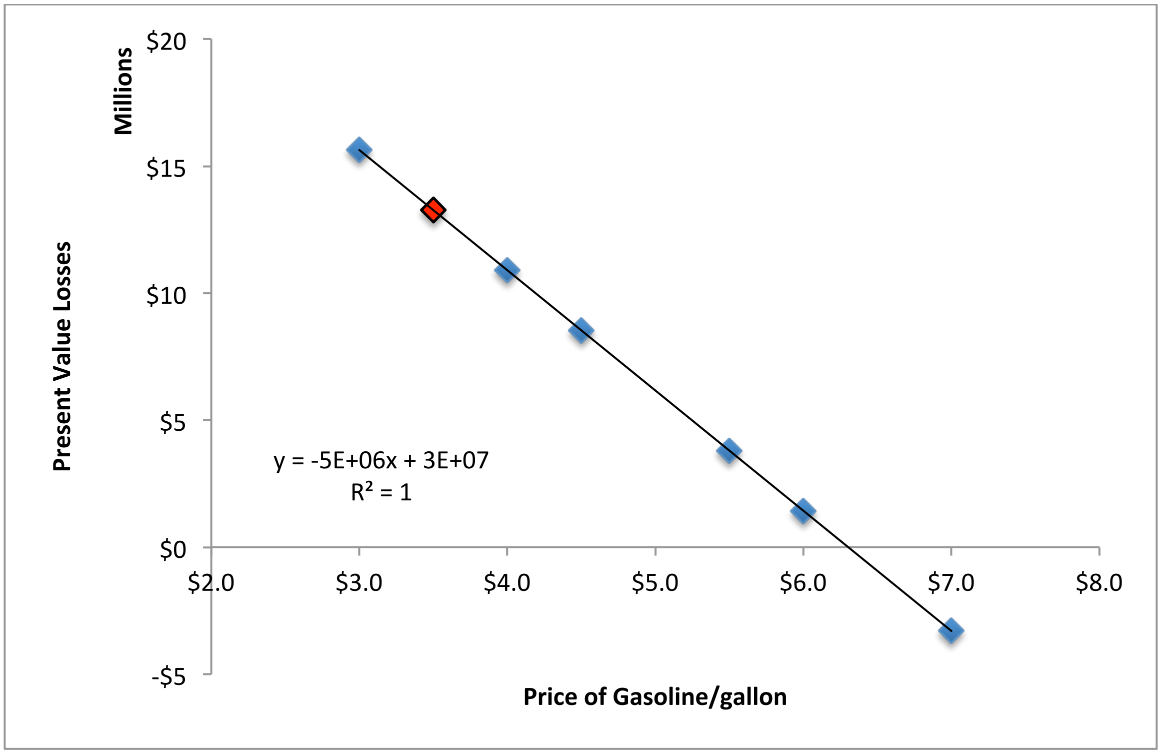


Figure 6-20 Sensitivity of Present Value losses to changes in gasoline price

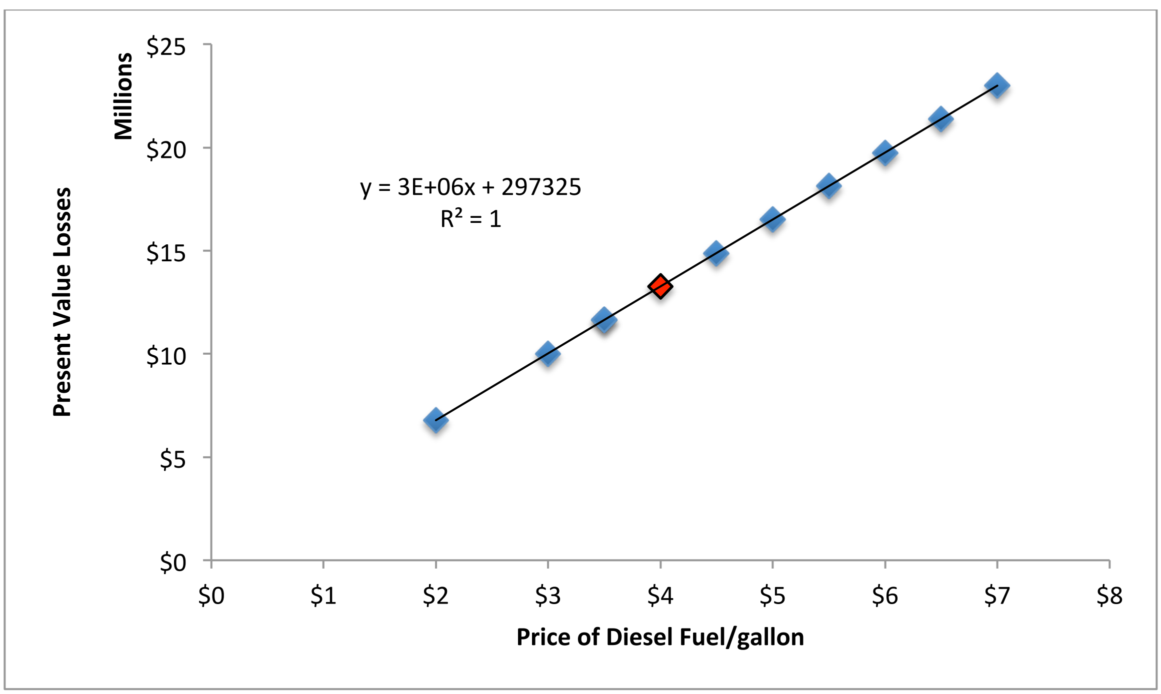


Figure 6-21 Sensitivity of Present Value losses to changes in diesel fuel price

In Figure 6-22, the impact of product prices on net present value is observed. Clearly, residual fuel oil price impacts the present value the most.

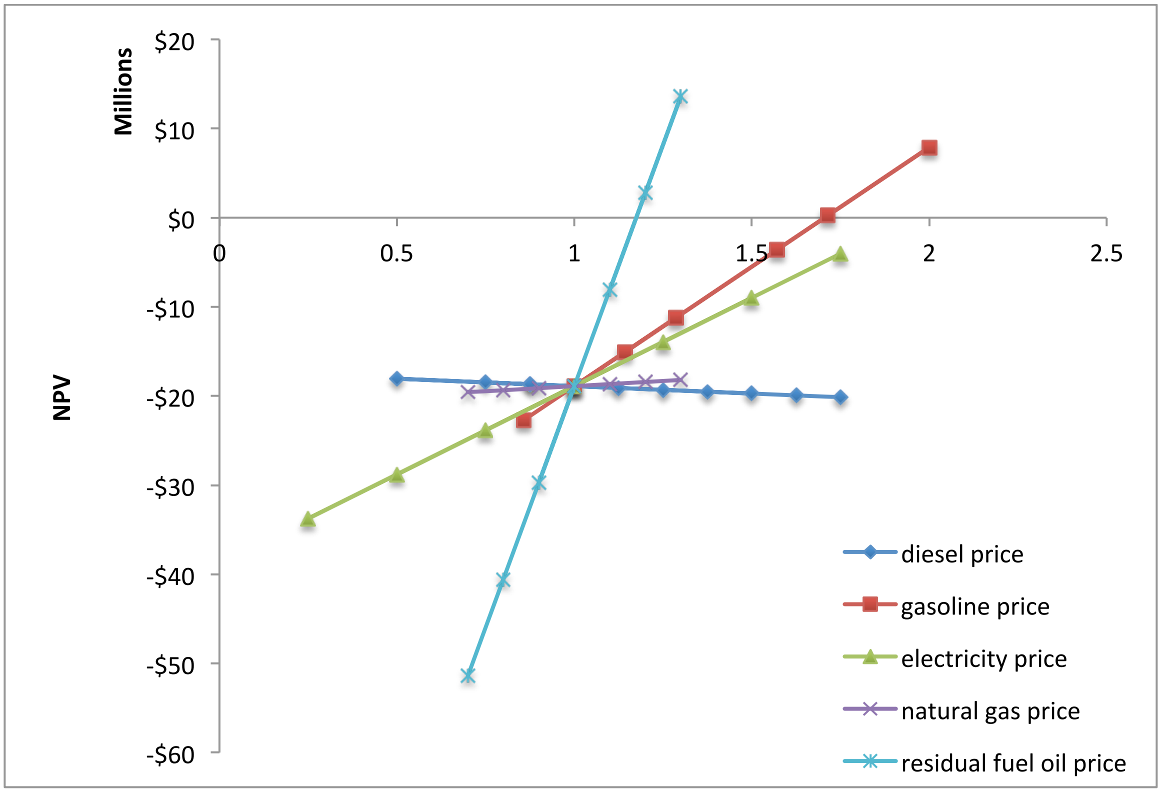


Figure 6-22 Sensitivity of Net Present Value losses to changes in product prices

To examine the impact each individual product sold by the biorefinery and determine potential areas for future work in product selection optimization, the net present value was examined given scenarios varying the product portfolio. The results obtained from simulation with the various indicated scenarios can be seen in Figure 6-23. The vertical axis was normalized to the net present value observed with a full product slate. From this chart it can be seen that the income from residual fuel oil sales has the largest impact on the net present value of the biorefinery supply chain. Also, the natural gas and even electricity income do not appear to be particularly significant. This insight can be fed back to the biorefinery chemical process simulation where utilities are being minimized.

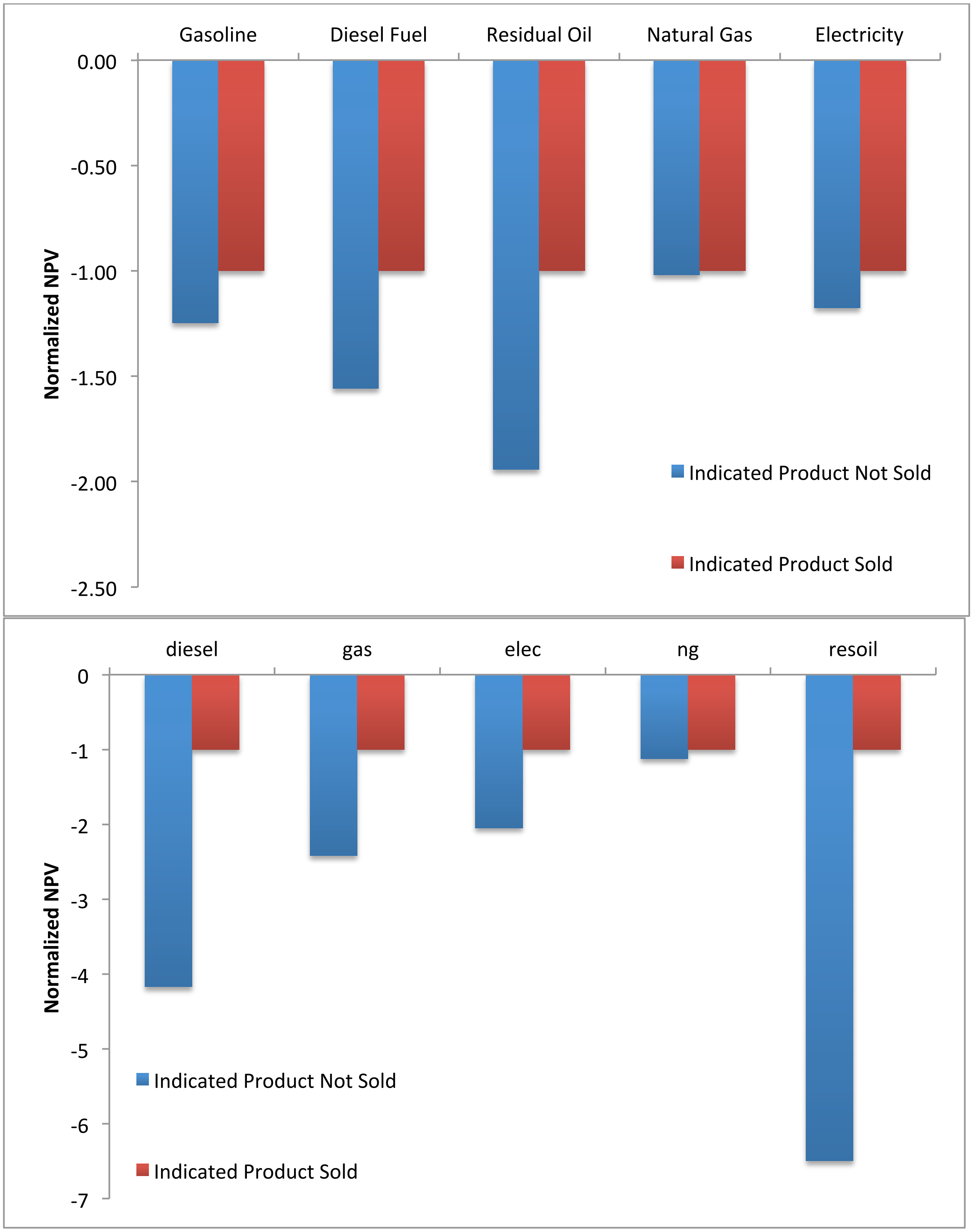


Figure 6-23 Impact of product portfolio on NPV

6.4 Examination of Costs

Of interest to this research is the breakdown of costs associated with biorefinery activities. These have been plotted and can be seen for the small and medium size biorefineries in Figures 6-24 and 6-25, respectively. As may be expected, the overall cost profile for the larger capacity biorefinery is higher; the profitable state of the medium size biorefinery can be attributed to increased income due to high production of residual fuel oil with unlimited demand assumed. In both cases, there is a clear drop in all costs corresponding to the beginning of the corn stover harvesting period. Here, inputs from the process modeling indicate a smaller biorefinery feedstock requirement relative to the rest of the year. As such, the biorefinery operating costs, transport costs, diesel costs, and raw material costs reflect this decision. Moving forward in time from the end of the corn stover harvest period, diesel costs used for the transportation of feedstock to the biorefinery and products to their final destination are significantly lowered. This reflects the biorefinery's ability to draw from the most optimal members of the optimal supply chain during this time period. As the year progresses from the end of one corn stover harvest to the next, it can be observed that the diesel expenses and the transport costs experienced by the biorefinery steadily increase as the biorefinery sources from farther distances. This finding is consistent with Faulkner (2012). Further insight into the system behavior, however can be gained from simulation. For instance, the costs observed during the entire simulation period have been plotted for the unprofitable small biorefinery in Figure 6-26. Here, the cyclic nature of various costs becomes evident. Similar patterns likely exist in reality for the operating costs. The relatively stable values seen for operating costs are due to the prescribed biorefinery specified operating costs. Specified feedstock requirements similarly explain the stable values observed for raw material costs. These particular variables could benefit from feedback communication in real time, perhaps informed by Bayesian belief network based risk analysis models or systems dynamics approaches, with the process simulation models; as of yet, such linkage of these separate models remains for future work.

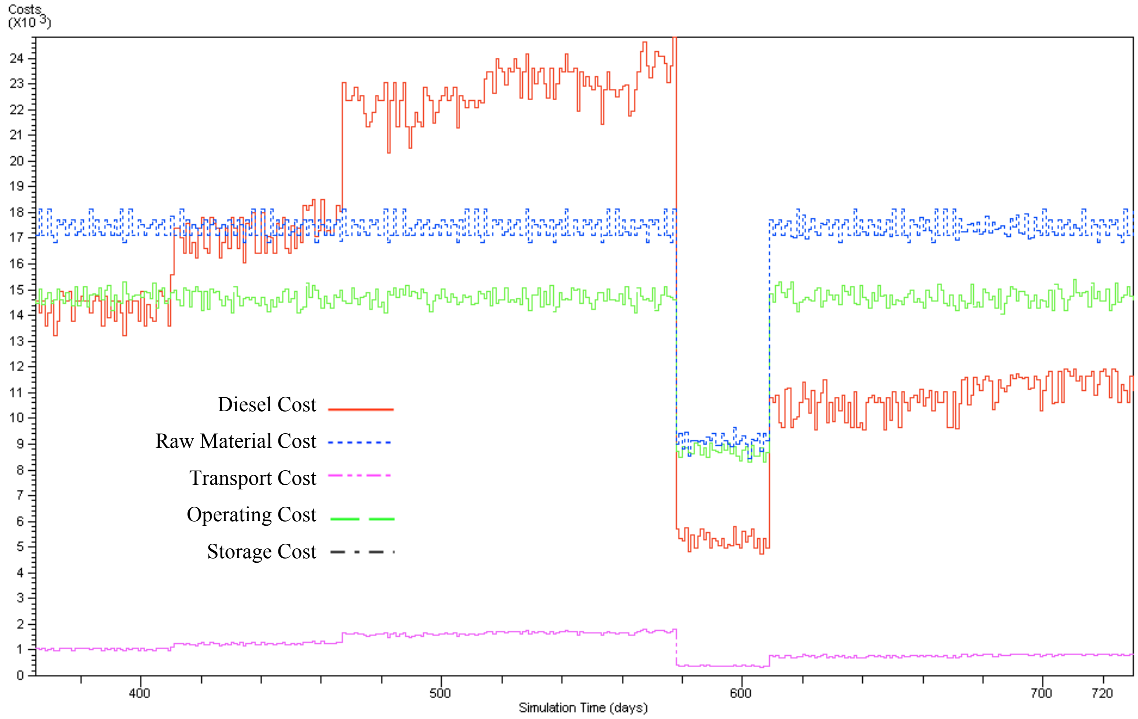


Figure 6-24 Costs over a representative year - small biorefinery.

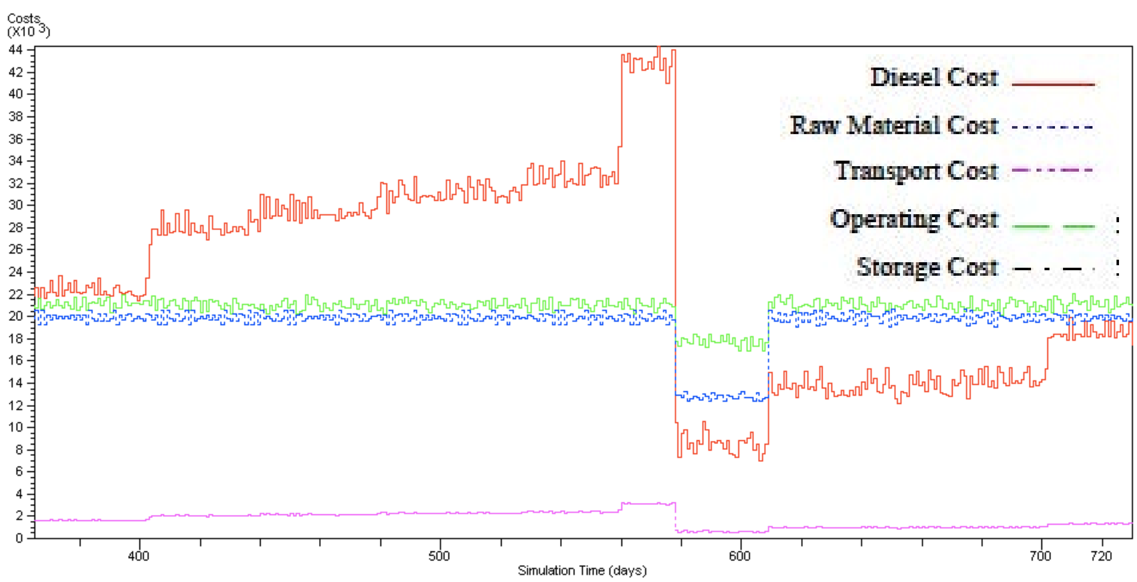


Figure 6-25 Costs over a representative year - medium biorefinery.

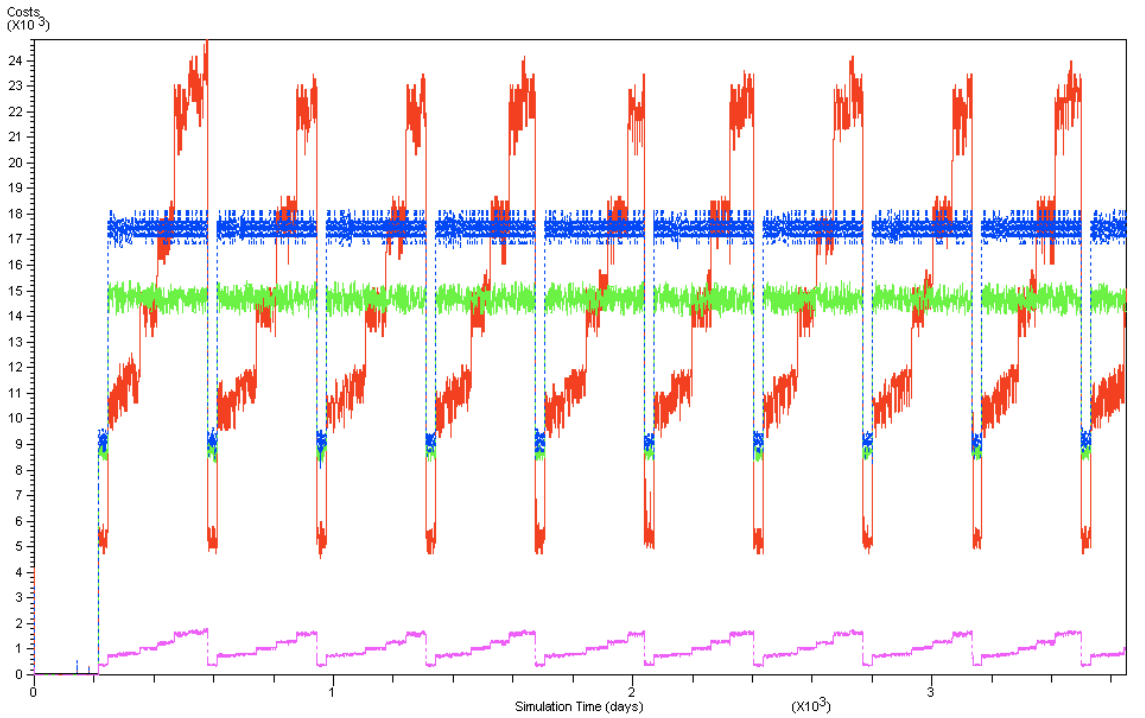


Figure 6-26 Costs over a simulation period (3650 days) - small biorefinery.

6.5 Scenario Analysis

This section discusses the use of the developed simulation model to examine means by which supply chain performance could be improved by technology adoption or by policy.

6.5.1 Inclusion of Preprocessing

The unprofitable small capacity biorefinery was selected for analysis in order to examine the possibility of improving its performance. Here, as was seen in Figure 6-15 and Figure 6-17, income made from product delivery to the marketplace is eliminated by large increases in diesel costs due to biomass feedstock exhaustion at nearby locations. To decrease the driving cost resulting in negative profitability one potential solution is the implementation of preprocessing at the biomass supply location. This activity effectively increases the density of the material to be transported by decreasing its volume. In this way, potentially more biomass could be shipped with fewer trucks and, therefore, smaller diesel costs for the biorefinery, assuming that entity funds the preprocessing activities.

Densification options can increase the bulk density of the loose biomass by at least half and up to ten times, depending on multiple factors (Sokhansanj and Turhollow, 2004). Although baling is a very common method for preparing biomass, particularly for residues like corn stover, to be transported, other options exist that allow for more densification of biomass at the feedstock location. Pelletization is one such methodology that has been shown to potentially increase the overall economics related to biomass supply chains (Usulu, et al 2008) with (Sultana et al, 2010) pelletization. Researchers have shown that pelletization can lead to significantly increased biomass shipment weight (Sokhansanj, et al (2010) for instance, reported biomass at 40 tons of corn stover per load compared to 12.35, the base case assumption). It seems obvious that decreasing the number of trucks in this way would have positive economic impacts. It is, however, important to consider the tradeoffs at play when implementing pelletization.

For this scenario analysis, Table 6-1 shows the assumptions used to implement preprocessing in the ARENA modeling. An additional variable was added to the ARENA model in order to track preprocessing costs as biomass is shipped from the corn stover source locations to the biorefinery.

Table 6-1 Assumed parameters to examine the feasibility of pelletization.

Source	Weight of Load (ton/load)	Price ($/ton processed)
Sokhansanj, et al (2010)	40	31

Figure 6-27 shows results from this analysis. The red curve indicates the benefits that can be realized by implementing preprocessing in the form of pelletization without taking into consideration the added costs. From the chart it is clear that improvements in net present value are achieved, however, for the scenario modeled via simulation, the gains achieved due to reduced diesel and transportation cost did not offset the increased costs associated with the pelletizing action. When the preprocessing costs associated with the simulated preprocessing activities is included in analysis, the deficit increases, making profitable supply chain activities more difficult to achieve.

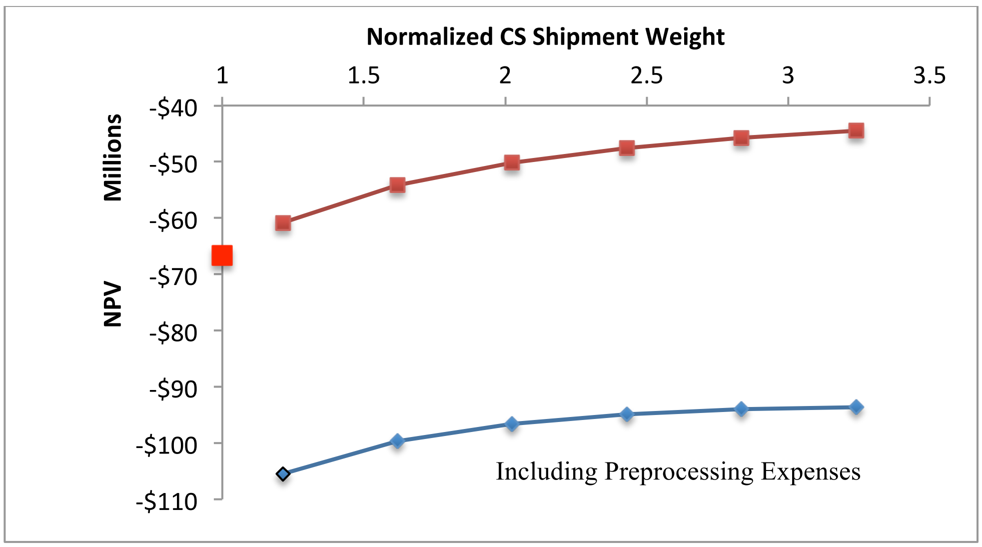


Figure 6-27 NPV as a function of increasing shipment weight

The improvement in performance can be attributed primarily to a marked decrease in the diesel costs associated with the delivery of corn stover to the biorefinery, as seen in Figure 6-28. The green line represents the diesel expenses when pelletizing is taking place; the red base case is the diesel cost associated with the delivery of un-processed corn stover. Relative decreases in transportation cost, diesel cost, and net losses (neglecting the additional cost of preprocessing activities) obtainable in this system can be seen in Figure 6-29.

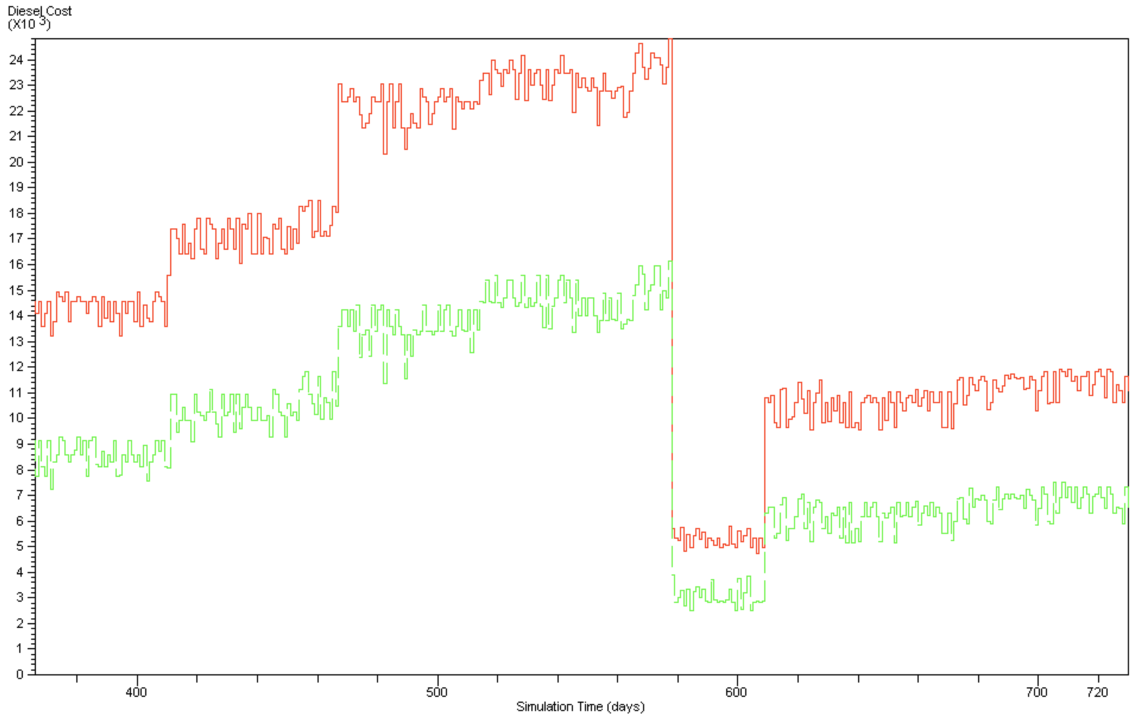


Figure 6-28 Decrease in diesel cost as a result of pelletizing corn stover

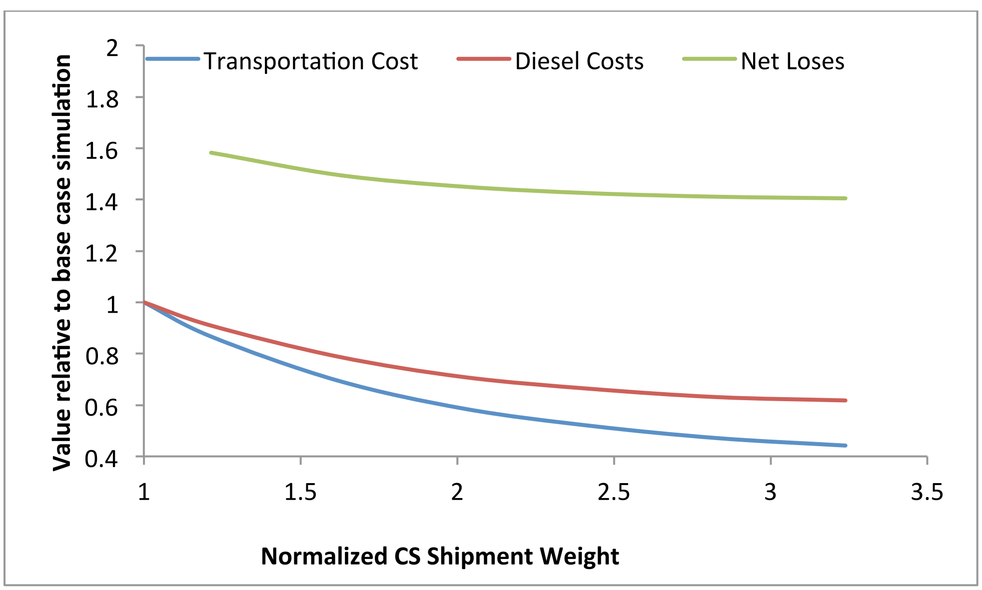


Figure 6-29 Costs as a function of shipment weight

6.5.2 Application of Subsidies

In 2009, as part of the Kentucky Governor's task force on biomass and biofuels in Kentucky (Anderson et al, 2009) it was suggested that public opinion of funding mechanisms to help foster a biomass based liquid fuel and energy industry in the state be assessed. The funding mechanisms suggested included a renewable energy fee on all electricity sold in the Commonwealth, reallocation of fees already assessed, revision of existing laws to allow for increased tax credits per gallon of biofuel produced, and public assistance in applications for federal loans and grants. For the purposes of demonstrating the ability of this simulation model to assess policy options, a scenario wherein a per gallon subsidy is provided by the state government to a biorefinery in the Jackson Purchase Region. KRS 141.4244 in Kentucky State law authorizes a $1/gallon tax credit for cellulosic ethanol production in the state. In the scenario, it has been assumed that this legislation has evolved such that the per gallon subsidy rate (SR) is applied after the production of any liquid fuels from renewable, lignocellulosic sources.

Various subsidy rates were applied in the small capacity biorefinery supply chain simulation model; the results can be seen in Figure 6-30. Applying linear regression, it is clear that for a subsidy rate of $1.75 per gallon of fuel produced is necessary cause the supply chain Net Present Value to break even. This analysis reveals that the current subsidy available, $1 per gallon of biodiesel or ethanol produced is not enough to support this biorefinery supply chain alone. However, the potential impact of this subsidy can be seen. If this rate were applied to all liquid fuel production, the $1/gallon produced would result in benefits of around $3 million per year. This level of sustained subsidy represents a potentially large burden on the tax paying population and, therefore, may not be a realistic alternative. However, this exercise is valuable in illustrating the insights for policy makers made available by this simulation model.

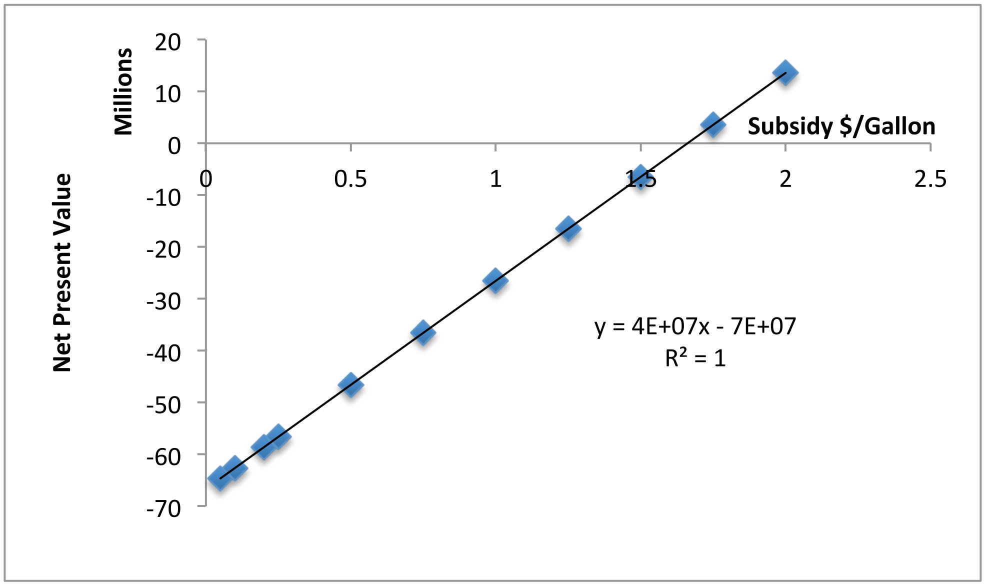


Figure 6-30 Impact of various subsidy rates on NPV – small biorefinery

7 CONCLUSIONS & FUTURE WORK

A comprehensive methodology for the development of a discrete event simulation model for the assessment of region specific biorefineries has been presented in this thesis. The simulation model utilized outputs from other models that constitute an integrated supply chain design framework, including supply chain optimization via MILP and chemical process simulation and optimization. The Jackson Purchase Region of Kentucky served as a case study to demonstrate the applicability of the simulation model in the context of the larger framework. The long-term economic performance of an optimized biorefinery supply chain was analyzed taking into consideration variability associated with lignocellulosic biomass feedstock supply and transportation fuel, natural gas, and electricity product demand. Based on the results of a previously completed MILP optimization model (Faulkner, 2012) two supply chain configurations with various feedstock consumption were considered for the case study. Both of the supply chains considered the conversion of second-generation lignocellulosic biomass including corn stover, chicken litter, and forest residue via gasification and Fischer-Tropsch synthesis in an integrated biorefinery. To properly simulate the availability of this atypical feedstock supply mixture, probability distributions for each county, for each month, for each feedstock were developed utilizing publically available historic data. The products considered included gasoline, diesel fuel, residual fuel oil, natural gas, and electricity. Similarly to the feedstock supply, regional demand for these goods had to be assessed and, subsequently, probability distributions had to be developed. By representing supply and demand with distributions formed by historic observations, a clearer picture of the time varying impact of the uncertainty inherent to biomass supply chains can be explored.

The current literature is lacking in biorefinery supply chain simulation models that take into account uncertainty inherent to the system. This research adds to this body of work by considering uncertainty in biomass supply and biorefinery product demand. Perhaps the most novel aspect about the presented model development is its role in a larger biorefinery supply chain design and optimization framework. Very few researchers have considered the interactions that exist among biorefinery supply chain design and chemical process modeling; even fewer have considered the role variability and uncertainty play in this context. This work, therefore, begins to bridge this gap.

Ultimately, as mentioned in this document's introduction, the goal of this work is to address the questions outlined in Section 1.1. The remainder of this chapter is organized according to activities aimed at addressing each of those questions.

7.1 Is an Optimized Biorefinery Supply Chain always Viable in a Given Region?

This work goes a long way toward answering this question. Analysis of the supply chains designated as optimal by Faulkner (2012) revealed many important insights. With very similar assumptions, it was shown that the small capacity integrated biorefinery was not profitable in the Jackson Purchase Region of Kentucky in the long run. Due to the granularity of the data used for input as well as the capabilities of the model, patterns in supply chain profitability could be discerned. In specific months following the harvest of corn stover the profit of the biorefinery increased dramatically due to large availability of nearby feedstock sources. As new material available each day declined and stocks held at the nearby feedstock supply locations were diminished through decay and usage for the production of final products, material had to be sourced from further locations. As the distance increased, costs associated with diesel fuel consumption and transportation related costs increased, resulting in increased losses. These results mirror the profitability shown by the model in Faulkner (2012). Projection of the discounted value of the investment several years into the future, however, revealed that despite these positive time periods, the overall profitability of the investment is extremely negative. This type of insight is only possible by considering the time-value of money over a long time horizon and incorporating variability in supply availability and product demand.

Similar analysis was conducted for the medium capacity facility. From Faulkner (2012) the medium capacity biorefinery supply chain was not profitable. However, due to assumptions related to the production and distribution of residual fuel oil, large profits for the biorefinery negated the increased losses from diesel fuel and transportation expenses. As per the suggestions in the methodology outlined by Faulkner (2012), it was assumed that, since residual fuel oil was a bunker fuel kept at the demand locations in bulk, demand for this product could be assumed to be infinite. In other words, it was assumed that all residual fuel oil had a buyer. In this thesis, it has been shown that by eliminating this assumption, the trend observed by Faulkner (2012) can be recreated with the simulation model.

7.2 How is the Profitability of a Biorefinery Supply Chain Impacted by Variability in Feedstock Supply Availability and Product Demand?

Sensitivity analysis was conducted for the simulation. It was determined that the most sensitive parameter in the simulation was the price of diesel fuel. Since the costs are shown to primarily be driven by the diesel expenses for the transportation of liquid fuel products and solid biomass feedstock, this result was expected. The impact of the sale of individual products was also examined. It was discovered that the sale of residual fuel oil has the largest influence on the net present value of the biorefinery supply chain. Perhaps more interestingly, the relatively small impacts of natural gas and electricity sale were discussed. This fact points to additional opportunities to design in recycle loops in the supply chain system. Utilizing the electricity and natural gas to offset operating costs associated with hot and cold utilities could potentially be more beneficial than the profits gained from the sale of these products. Similarly, further analysis examining the use of part or all of the produced diesel fuel for transporting feedstocks and products would be beneficial. This exploration would reveal any potential benefits available by offsetting the expense of purchasing this product for use in transportation activities. There likely exists some optimal combination of diesel fuel self-consumption and sales; employing an optimal policy could potentially yield a more economically sustainable biorefinery supply chain.

In the current application, uncertainty with regards to biomass supply and product demand is taken into consideration through the use of probability distributions based on historical observations. In future, research should help to develop models with predictive capabilities as well. Incorporation of a robust Bayesian Belief Network based quantitative, probabilistic risk model, similar to that discussed in Amundson et al (2012, 2013), could help to provide insight for such an addition to the model. In this way, events occurring in the discrete event simulation model could provide evidence to update the historically based data distributions resulting in a more realistic representation of the supply chain dynamics. Other methodologies, particularly systems dynamics, could be employed to help inform the evolution of the values of model parameters with time. Macroeconomic effects and emergent behavior in the system as the biofuel and bioenergy markets mature could be explored, among many other possibilities.

7.3 In what ways could the modeled supply chain be improved for long term positive economic performance?

After analysis uncovered the dependence of biorefinery profitability on the diesel fuel expenses required to transport both feedstock and products, the impact of including biomass densification activities in the supply chain was explored. In theory, by increasing the weight of each shipment of corn stover via densification of the biomass, there should be a reduction in diesel fuel consumption. Due to the fact that diesel consumption in the simulation model is dependent on weight of the shipment, some optimal level of densification must exist. In practice, the decreases in diesel fuel consumption do result in improved values of NPV. However, it was found that, for the modeled scenario, the gains realized did not eclipse the necessary costs associated with the preprocessing activities. In fact, the ultimate effect of adding preprocessing costs was a negative shift in the NPV that resulted in worse economic performance for the biorefinery. In certain situations, where the number of shipment is very high due to very high volume production, for instance, the fuel savings would be amplified and the expenses could be overcome driven by increased profits and decreased costs. However, these results were not observed for the presented case study in the Jackson Purchase Region.

Currently, a major limitation in the application of the multidisciplinary biorefinery supply chain decision support framework visualized in Figure 3-1 is the breadth of lignocellulosic biomass to fuel technologies considered. In this thesis, the simulation model assumed the application of an integrated biorefinery utilizing gasification, water-gas shift, and Fischer-Tropsch synthesis. Future work should develop a library of chemical process models that the supply chain optimization and simulation models could draw from. In this way, multiple alternative technology platforms could be considered for a given region and the most viable could be selected based on the dynamic conditions in the simulation model. A good justification for this approach can be seen through the ethanol production via dilute-acid pretreatment, saccharificaation, and fermentation discussed in Faulkner (2012). Compared with the integrated biorefinery, this process, based on literature rather than results from process simulation, showed more consistently profitable performance in the given region. Integration of this model with process simulation and optimization and the supply chain simulation model discussed here could potentially yield more profitable results for a region specific biorefinery supply chain.

7.4 How can policy decisions impact the viability of regional biorefinery supply chains?

To demonstrate the simulation model's capacity for testing the impact of policy measures on the profitability of a designed biomass supply chain, options for policy measures were first examined. Figure 1-2 outlines the various state level legislations in the United States related to woody biomass. Existing incentive programs in Kentucky, it was discovered, allow for a tax credit of one dollar per gallon of biodiesel/ethanol produced or blended in the state. It has been assumed that this tax credit corresponds to an equal increase in the biorefinery profit without impacting costs; therefore, it is assumed that these subsidies result in increases the net present value of the investment. For the purposes of demonstrating applicability, it has been assumed that regional governments would extend the biodiesel and ethanol subsidy to any liquid fuel product produced form lignocelluloisc biomass.

It was observed that, in general, the addition of subsidies in this way results in an increase of the net present value proportional to the total production of fuels. This means that the larger the volume of product created, the larger the subsidy. However, it was previously shown that large capacity biorefineries in the Jackson Purchase Region are not profitable due to limited locally available biomass. An optimization problem could be solved to potentially find an optimal combination of biomass transportation activity and subsidy rates. Additionally, future work should address means of subsidy application other than a direct subsidy per gallon of product. Considerations such transportation related subsidies or incentives based on capital investment could be made for a more complete analysis.

Ultimately, the simulation provides a first step toward analyzing the sustainability of biomass supply chains. Further refinements mentioned throughout this section could help increase the usefulness and accuracy of the data obtained from the model. Additionally, simulation and optimization modeling in the multidisciplinary framework should incorporate decision variables that minimize negative environmental and societal impacts. For instance, incorporation of soil erosion and emissions calculations into the portions of the simulation where biomass supply is generated and transported, with feedback to limit them to a sustainable level, would help to minimize environmental impact. System dynamics models integrated with the discrete event simulation could quantify societal impacts of the biorefinery supply chain such as rural development, local employment, and the degree of reliance on fossil fuel in a region of interest. Additional heat and mass integration in the chemical process simulation and optimization models could help improve the operational costs as well as the environmental impact of the biorefinery. Taking all this into consideration, a powerful insight for biorefinery supply chain decision makers could potentially be gained through the use of this simulation model in conjunction with the multidisciplinary framework.

Appendix A: Processed Corn Harvest Data

Data synthesized from USDA, 2010b and USDA, 2010a via equations 5-1 through 5-3

Week of…	Ballard	Calloway	Carlisle	Fulton	Graves	Hickman	Marshall	McCracken
27-Aug	4,143.10	4,326.22	3,649.52	5,394.93	8,177.57	6,016.64	1,391.04	1,881.60
3-Sep	6,214.66	6,489.34	5,474.28	8,092.39	12,266.35	9,024.96	2,086.56	2,822.40
10-Sep	11,393.54	11,897.12	10,036.18	14,836.05	22,488.31	16,545.76	3,825.36	5,174.40
17-Sep	12,429.31	12,978.67	10,948.56	16,184.78	24,532.70	18,049.92	4,173.12	5,644.80
24-Sep	17,608.19	18,386.45	15,510.46	22,928.44	34,754.66	25,570.72	5,911.92	7,996.80
1-Oct	14,500.86	15,141.78	12,773.32	18,882.25	28,621.49	21,058.24	4,868.64	6,585.60
8-Oct	18,643.97	19,468.01	16,422.84	24,277.18	36,799.06	27,074.88	6,259.68	8,467.20
15-Oct	5,178.88	5,407.78	4,561.90	6,743.66	10,221.96	7,520.80	1,738.80	2,352.00
22-Oct	3,107.33	3,244.67	2,737.14	4,046.20	6,133.18	4,512.48	1,043.28	1,411.20
29-Oct	4,143.10	4,326.22	3,649.52	5,394.93	8,177.57	6,016.64	1,391.04	1,881.60
5-Nov	3,107.33	3,244.67	2,737.14	4,046.20	6,133.18	4,512.48	1,043.28	1,411.20
26-Aug	5,008.78	7,375.34	4,234.72	6,660.64	11,252.08	8,008.00	1,679.58	2,880.36
2-Sep	7,012.29	10,325.48	5,928.61	9,324.90	15,752.91	11,211.20	2,351.41	4,032.50
9-Sep	8,014.05	11,800.54	6,775.55	10,657.02	18,003.33	12,812.80	2,687.33	4,608.58
16-Sep	10,017.56	14,750.68	8,469.44	13,321.28	22,504.16	16,016.00	3,359.16	5,760.72
23-Sep	20,035.12	29,501.36	16,938.88	26,642.56	45,008.32	32,032.00	6,718.32	11,521.44
30-Sep	19,033.36	28,026.29	16,091.94	25,310.43	42,757.90	30,430.40	6,382.40	10,945.37
7-Oct	19,033.36	28,026.29	16,091.94	25,310.43	42,757.90	30,430.40	6,382.40	10,945.37
14-Oct	2,003.51	2,950.14	1,693.89	2,664.26	4,500.83	3,203.20	671.83	1,152.14
21-Oct	2,003.51	2,950.14	1,693.89	2,664.26	4,500.83	3,203.20	671.83	1,152.14
28-Oct	4,007.02	5,900.27	3,387.78	5,328.51	9,001.66	6,406.40	1,343.66	2,304.29
4-Nov	2,003.51	2,950.14	1,693.89	2,664.26	4,500.83	3,203.20	671.83	1,152.14
25-Aug	5,733.50	9,749.88	6,264.72	7,476.84	16,808.40	10,712.52	2,407.86	2,364.77
1-Sep	7,007.62	11,916.52	7,656.88	9,138.36	20,543.60	13,093.08	2,942.94	2,890.27
8-Sep	9,555.84	16,249.80	10,441.20	12,461.40	28,014.00	17,854.20	4,013.10	3,941.28
15-Sep	7,644.67	12,999.84	8,352.96	9,969.12	22,411.20	14,283.36	3,210.48	3,153.02
22-Sep	6,370.56	10,833.20	6,960.80	8,307.60	18,676.00	11,902.80	2,675.40	2,627.52
29-Sep	3,822.34	6,499.92	4,176.48	4,984.56	11,205.60	7,141.68	1,605.24	1,576.51
6-Oct	9,555.84	16,249.80	10,441.20	12,461.40	28,014.00	17,854.20	4,013.10	3,941.28
13-Oct	5,733.50	9,749.88	6,264.72	7,476.84	16,808.40	10,712.52	2,407.86	2,364.77
20-Oct	1,911.17	3,249.96	2,088.24	2,492.28	5,602.80	3,570.84	802.62	788.26
27-Oct	2,548.22	4,333.28	2,784.32	3,323.04	7,470.40	4,761.12	1,070.16	1,051.01
3-Nov	1,911.17	3,249.96	2,088.24	2,492.28	5,602.80	3,570.84	802.62	788.26

29-Aug	6,281.86	7,822.92	5,769.46	7,319.09	14,410.70	11,238.86	2,086.56	3,752.78
5-Sep	4,187.90	5,215.28	3,846.30	4,879.39	9,607.14	7,492.58	1,391.04	2,501.86
12-Sep	18,845.57	23,468.76	17,308.37	21,957.26	43,232.11	33,716.59	6,259.68	11,258.35
19-Sep	10,469.76	13,038.20	9,615.76	12,198.48	24,017.84	18,731.44	3,477.60	6,254.64
26-Sep	19,892.54	24,772.58	18,269.94	23,177.11	45,633.90	35,589.74	6,607.44	11,883.82
3-Oct	12,563.71	15,645.84	11,538.91	14,638.18	28,821.41	22,477.73	4,173.12	7,505.57
10-Oct	14,657.66	18,253.48	13,462.06	17,077.87	33,624.98	26,224.02	4,868.64	8,756.50
17-Oct	5,234.88	6,519.10	4,807.88	6,099.24	12,008.92	9,365.72	1,738.80	3,127.32
24-Oct	4,187.90	5,215.28	3,846.30	4,879.39	9,607.14	7,492.58	1,391.04	2,501.86
31-Oct	3,140.93	3,911.46	2,884.73	3,659.54	7,205.35	5,619.43	1,043.28	1,876.39
7-Nov	2,093.95	2,607.64	1,923.15	2,439.70	4,803.57	3,746.29	695.52	1,250.93
4-Sep	9,756.18	11,999.23	8,135.32	9,713.09	22,289.40	15,262.13	3,131.35	4,938.95
11-Sep	6,504.12	7,999.49	5,423.54	6,475.39	14,859.60	10,174.75	2,087.57	3,292.63
18-Sep	17,344.32	21,331.97	14,462.78	17,267.71	39,625.60	27,132.67	5,566.85	8,780.35
25-Sep	18,428.34	22,665.22	15,366.71	18,346.94	42,102.20	28,828.46	5,914.78	9,329.12
2-Oct	19,512.36	23,998.46	16,270.63	19,426.18	44,578.80	30,524.26	6,262.70	9,877.90
9-Oct	15,176.28	18,665.47	12,654.94	15,109.25	34,672.40	23,741.09	4,870.99	7,682.81
16-Oct	8,672.16	10,665.98	7,231.39	8,633.86	19,812.80	13,566.34	2,783.42	4,390.18
23-Oct	5,420.10	6,666.24	4,519.62	5,396.16	12,383.00	8,478.96	1,739.64	2,743.86
30-Oct	6,504.12	7,999.49	5,423.54	6,475.39	14,859.60	10,174.75	2,087.57	3,292.63
6-Nov	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
13-Nov	1,084.02	1,333.25	903.92	1,079.23	2,476.60	1,695.79	347.93	548.77
3-Sep	12,265.68	15,124.70	11,176.70	10,405.92	25,346.16	19,509.50	2,787.46	5,685.12
10-Sep	6,132.84	7,562.35	5,588.35	5,202.96	12,673.08	9,754.75	1,393.73	2,842.56
17-Sep	11,243.54	13,864.31	10,245.31	9,538.76	23,233.98	17,883.71	2,555.17	5,211.36
24-Sep	10,221.40	12,603.92	9,313.92	8,671.60	21,121.80	16,257.92	2,322.88	4,737.60
1-Oct	14,309.96	17,645.49	13,039.49	12,140.24	29,570.52	22,761.09	3,252.03	6,632.64
8-Oct	15,332.10	18,905.88	13,970.88	13,007.40	31,682.70	24,386.88	3,484.32	7,106.40
15-Oct	14,309.96	17,645.49	13,039.49	12,140.24	29,570.52	22,761.09	3,252.03	6,632.64
22-Oct	3,066.42	3,781.18	2,794.18	2,601.48	6,336.54	4,877.38	696.86	1,421.28
29-Oct	6,132.84	7,562.35	5,588.35	5,202.96	12,673.08	9,754.75	1,393.73	2,842.56
5-Nov	2,044.28	2,520.78	1,862.78	1,734.32	4,224.36	3,251.58	464.58	947.52
12-Nov	6,132.84	7,562.35	5,588.35	5,202.96	12,673.08	9,754.75	1,393.73	2,842.56
2-Sep	9,321.98	9,734.00	8,211.42	12,138.59	18,399.53	13,537.44	3,129.84	4,233.60
9-Sep	10,357.76	10,815.56	9,123.80	13,487.32	20,443.92	15,041.60	3,477.60	4,704.00
16-Sep	13,465.09	14,060.23	11,860.94	17,533.52	26,577.10	19,554.08	4,520.88	6,115.20
23-Sep	16,572.42	17,304.90	14,598.08	21,579.71	32,710.27	24,066.56	5,564.16	7,526.40
30-Sep	14,500.86	15,141.78	12,773.32	18,882.25	28,621.49	21,058.24	4,868.64	6,585.60
7-Oct	17,608.19	18,386.45	15,510.46	22,928.44	34,754.66	25,570.72	5,911.92	7,996.80
14-Oct	8,286.21	8,652.45	7,299.04	10,789.86	16,355.14	12,033.28	2,782.08	3,763.20
21-Oct	3,107.33	3,244.67	2,737.14	4,046.20	6,133.18	4,512.48	1,043.28	1,411.20
28-Oct	4,143.10	4,326.22	3,649.52	5,394.93	8,177.57	6,016.64	1,391.04	1,881.60

4-Nov	4,143.10	4,326.22	3,649.52	5,394.93	8,177.57	6,016.64	1,391.04	1,881.60
25-Aug	5,008.78	7,375.34	4,234.72	6,660.64	11,252.08	8,008.00	1,679.58	2,880.36
1-Sep	5,008.78	7,375.34	4,234.72	6,660.64	11,252.08	8,008.00	1,679.58	2,880.36
8-Sep	9,015.80	13,275.61	7,622.50	11,989.15	20,253.74	14,414.40	3,023.24	5,184.65
15-Sep	10,017.56	14,750.68	8,469.44	13,321.28	22,504.16	16,016.00	3,359.16	5,760.72
22-Sep	18,031.61	26,551.22	15,244.99	23,978.30	40,507.49	28,828.80	6,046.49	10,369.30
29-Sep	18,031.61	26,551.22	15,244.99	23,978.30	40,507.49	28,828.80	6,046.49	10,369.30
6-Oct	18,031.61	26,551.22	15,244.99	23,978.30	40,507.49	28,828.80	6,046.49	10,369.30
13-Oct	7,012.29	10,325.48	5,928.61	9,324.90	15,752.91	11,211.20	2,351.41	4,032.50
20-Oct	2,003.51	2,950.14	1,693.89	2,664.26	4,500.83	3,203.20	671.83	1,152.14
27-Oct	3,005.27	4,425.20	2,540.83	3,996.38	6,751.25	4,804.80	1,007.75	1,728.22
3-Nov	3,005.27	4,425.20	2,540.83	3,996.38	6,751.25	4,804.80	1,007.75	1,728.22
31-Aug	11,467.01	19,499.76	12,529.44	14,953.68	33,616.80	21,425.04	4,815.72	4,729.54
7-Sep	9,555.84	16,249.80	10,441.20	12,461.40	28,014.00	17,854.20	4,013.10	3,941.28
14-Sep	7,644.67	12,999.84	8,352.96	9,969.12	22,411.20	14,283.36	3,210.48	3,153.02
21-Sep	6,370.56	10,833.20	6,960.80	8,307.60	18,676.00	11,902.80	2,675.40	2,627.52
28-Sep	3,822.34	6,499.92	4,176.48	4,984.56	11,205.60	7,141.68	1,605.24	1,576.51
5-Oct	9,555.84	16,249.80	10,441.20	12,461.40	28,014.00	17,854.20	4,013.10	3,941.28
12-Oct	6,370.56	10,833.20	6,960.80	8,307.60	18,676.00	11,902.80	2,675.40	2,627.52
19-Oct	1,911.17	3,249.96	2,088.24	2,492.28	5,602.80	3,570.84	802.62	788.26
26-Oct	1,911.17	3,249.96	2,088.24	2,492.28	5,602.80	3,570.84	802.62	788.26
2-Nov	3,185.28	5,416.60	3,480.40	4,153.80	9,338.00	5,951.40	1,337.70	1,313.76
9-Nov	1,274.11	2,166.64	1,392.16	1,661.52	3,735.20	2,380.56	535.08	525.50
4-Sep	9,422.78	11,734.38	8,654.18	10,978.63	21,616.06	16,858.30	3,129.84	5,629.18
11-Sep	17,798.59	22,164.94	16,346.79	20,737.42	40,830.33	31,843.45	5,911.92	10,632.89
18-Sep	10,469.76	13,038.20	9,615.76	12,198.48	24,017.84	18,731.44	3,477.60	6,254.64
25-Sep	17,798.59	22,164.94	16,346.79	20,737.42	40,830.33	31,843.45	5,911.92	10,632.89
2-Oct	14,657.66	18,253.48	13,462.06	17,077.87	33,624.98	26,224.02	4,868.64	8,756.50
9-Oct	14,657.66	18,253.48	13,462.06	17,077.87	33,624.98	26,224.02	4,868.64	8,756.50
16-Oct	6,281.86	7,822.92	5,769.46	7,319.09	14,410.70	11,238.86	2,086.56	3,752.78
23-Oct	4,187.90	5,215.28	3,846.30	4,879.39	9,607.14	7,492.58	1,391.04	2,501.86
30-Oct	4,187.90	5,215.28	3,846.30	4,879.39	9,607.14	7,492.58	1,391.04	2,501.86
6-Nov	2,093.95	2,607.64	1,923.15	2,439.70	4,803.57	3,746.29	695.52	1,250.93
13-Nov	2,093.95	2,607.64	1,923.15	2,439.70	4,803.57	3,746.29	695.52	1,250.93
3-Sep	8,672.16	10,665.98	7,231.39	8,633.86	19,812.80	13,566.34	2,783.42	4,390.18
10-Sep	6,504.12	7,999.49	5,423.54	6,475.39	14,859.60	10,174.75	2,087.57	3,292.63
17-Sep	16,260.30	19,998.72	13,558.86	16,188.48	37,149.00	25,436.88	5,218.92	8,231.58
24-Sep	29,268.54	35,997.70	24,405.95	29,139.26	66,868.20	45,786.38	9,394.06	14,816.84
1-Oct	7,588.14	9,332.74	6,327.47	7,554.62	17,336.20	11,870.54	2,435.50	3,841.40

8-Oct	16,260.30	19,998.72	13,558.86	16,188.48	37,149.00	25,436.88	5,218.92	8,231.58
15-Oct	10,840.20	13,332.48	9,039.24	10,792.32	24,766.00	16,957.92	3,479.28	5,487.72
22-Oct	5,420.10	6,666.24	4,519.62	5,396.16	12,383.00	8,478.96	1,739.64	2,743.86
29-Oct	5,420.10	6,666.24	4,519.62	5,396.16	12,383.00	8,478.96	1,739.64	2,743.86
5-Nov	1,084.02	1,333.25	903.92	1,079.23	2,476.60	1,695.79	347.93	548.77
12-Nov	1,084.02	1,333.25	903.92	1,079.23	2,476.60	1,695.79	347.93	548.77
1-Sep	9,321.98	9,734.00	8,211.42	12,138.59	18,399.53	13,537.44	3,129.84	4,233.60
8-Sep	9,321.98	9,734.00	8,211.42	12,138.59	18,399.53	13,537.44	3,129.84	4,233.60
15-Sep	12,429.31	12,978.67	10,948.56	16,184.78	24,532.70	18,049.92	4,173.12	5,644.80
22-Sep	16,572.42	17,304.90	14,598.08	21,579.71	32,710.27	24,066.56	5,564.16	7,526.40
29-Sep	14,500.86	15,141.78	12,773.32	18,882.25	28,621.49	21,058.24	4,868.64	6,585.60
6-Oct	17,608.19	18,386.45	15,510.46	22,928.44	34,754.66	25,570.72	5,911.92	7,996.80
13-Oct	9,321.98	9,734.00	8,211.42	12,138.59	18,399.53	13,537.44	3,129.84	4,233.60
20-Oct	4,143.10	4,326.22	3,649.52	5,394.93	8,177.57	6,016.64	1,391.04	1,881.60
27-Oct	4,143.10	4,326.22	3,649.52	5,394.93	8,177.57	6,016.64	1,391.04	1,881.60
3-Nov	3,107.33	3,244.67	2,737.14	4,046.20	6,133.18	4,512.48	1,043.28	1,411.20
31-Aug	9,015.80	13,275.61	7,622.50	11,989.15	20,253.74	14,414.40	3,023.24	5,184.65
7-Sep	9,015.80	13,275.61	7,622.50	11,989.15	20,253.74	14,414.40	3,023.24	5,184.65
14-Sep	9,015.80	13,275.61	7,622.50	11,989.15	20,253.74	14,414.40	3,023.24	5,184.65
21-Sep	17,029.85	25,076.16	14,398.05	22,646.18	38,257.07	27,227.20	5,710.57	9,793.22
28-Sep	18,031.61	26,551.22	15,244.99	23,978.30	40,507.49	28,828.80	6,046.49	10,369.30
5-Oct	20,035.12	29,501.36	16,938.88	26,642.56	45,008.32	32,032.00	6,718.32	11,521.44
12-Oct	6,010.54	8,850.41	5,081.66	7,992.77	13,502.50	9,609.60	2,015.50	3,456.43
19-Oct	2,003.51	2,950.14	1,693.89	2,664.26	4,500.83	3,203.20	671.83	1,152.14
26-Oct	4,007.02	5,900.27	3,387.78	5,328.51	9,001.66	6,406.40	1,343.66	2,304.29
2-Nov	3,005.27	4,425.20	2,540.83	3,996.38	6,751.25	4,804.80	1,007.75	1,728.22
9-Nov	1,001.76	1,475.07	846.94	1,332.13	2,250.42	1,601.60	335.92	576.07
29-Aug	10,192.90	17,333.12	11,137.28	13,292.16	29,881.60	19,044.48	4,280.64	4,204.03
5-Sep	8,281.73	14,083.16	9,049.04	10,799.88	24,278.80	15,473.64	3,478.02	3,415.78
12-Sep	8,281.73	14,083.16	9,049.04	10,799.88	24,278.80	15,473.64	3,478.02	3,415.78
19-Sep	7,007.62	11,916.52	7,656.88	9,138.36	20,543.60	13,093.08	2,942.94	2,890.27
26-Sep	4,459.39	7,583.24	4,872.56	5,815.32	13,073.20	8,331.96	1,872.78	1,839.26
3-Oct	7,644.67	12,999.84	8,352.96	9,969.12	22,411.20	14,283.36	3,210.48	3,153.02
10-Oct	7,007.62	11,916.52	7,656.88	9,138.36	20,543.60	13,093.08	2,942.94	2,890.27
17-Oct	3,185.28	5,416.60	3,480.40	4,153.80	9,338.00	5,951.40	1,337.70	1,313.76
24-Oct	1,911.17	3,249.96	2,088.24	2,492.28	5,602.80	3,570.84	802.62	788.26
31-Oct	2,548.22	4,333.28	2,784.32	3,323.04	7,470.40	4,761.12	1,070.16	1,051.01
7-Nov	1,911.17	3,249.96	2,088.24	2,492.28	5,602.80	3,570.84	802.62	788.26
3-Sep	9,422.78	11,734.38	8,654.18	10,978.63	21,616.06	16,858.30	3,129.84	5,629.18
10-Sep	13,610.69	16,949.66	12,500.49	15,858.02	31,223.19	24,350.87	4,520.88	8,131.03
17-Sep	13,610.69	16,949.66	12,500.49	15,858.02	31,223.19	24,350.87	4,520.88	8,131.03
24-Sep	16,751.62	20,861.12	15,385.22	19,517.57	38,428.54	29,970.30	5,564.16	10,007.42

1-Oct	15,704.64	19,557.30	14,423.64	18,297.72	36,026.76	28,097.16	5,216.40	9,381.96
8-Oct	13,610.69	16,949.66	12,500.49	15,858.02	31,223.19	24,350.87	4,520.88	8,131.03
15-Oct	9,422.78	11,734.38	8,654.18	10,978.63	21,616.06	16,858.30	3,129.84	5,629.18
22-Oct	4,187.90	5,215.28	3,846.30	4,879.39	9,607.14	7,492.58	1,391.04	2,501.86
29-Oct	2,093.95	2,607.64	1,923.15	2,439.70	4,803.57	3,746.29	695.52	1,250.93
5-Nov	2,093.95	2,607.64	1,923.15	2,439.70	4,803.57	3,746.29	695.52	1,250.93
12-Nov	2,093.95	2,607.64	1,923.15	2,439.70	4,803.57	3,746.29	695.52	1,250.93

APPENDIX B: DISTANCE ARRAY DATA

Corn Stover									
No.	Biorefinery / Supply	Ballard	Calloway	Carlisle	Fulton	Graves	Hickman	Marshall	McCracken
1	Ballard	21	69.8	29.6	61.9	42.8	44.1	48.8	22.5
2		8.7	72.3	17.2	49.6	39.7	32.1	53.6	28.1
3		9.1	52.2	14.6	46.9	28.3	29.4	45.4	23.5
4		15.3	62.6	23.9	56.2	37	38.8	44	18.4
5	Calloway	60.3	5.3	55.8	56.4	29.7	50.5	23.9	52.2
6		50.1	9.7	45.6	55.1	19.5	40.7	15.9	34.6
7		55.4	7.9	50.9	50.7	24.8	44.7	26.5	54.8
8	Carlisle	11	44.1	6.5	38.8	20.2	21.3	37.5	29.7
9		14.7	46.7	6.2	35.8	22.8	18.3	40.1	34.1
10		13.2	53.9	4.7	27.7	25.1	10.2	48.6	38.9
11	Fulton	42.9	51.9	34.3	3.4	39.4	19.4	58.5	68.5
12		33	42.3	24.4	8.9	32.1	9.5	51.2	61.2
13		37.6	48	29.1	5.7	37.8	14.2	56.9	66.9
14		33.9	35.5	25.4	16.5	24.6	10.5	43.7	53.7
15	Graves	43.5	17.1	39	37.6	12.9	31.6	30.3	40.3
16		42.3	26.4	33.7	24.8	20.6	18.9	39.6	49.7
17		38.1	19.2	33.6	39.6	7.5	27.9	24.9	34.9
18		23	36.6	18.4	52.4	12.7	28.6	29.3	20
19		29.1	32	21.2	36.6	10.6	17.5	29.6	39.6
20		30.7	30.3	26.2	49.4	7.7	32	20.8	18.8
21		37.8	18.8	33.2	49.2	7.1	29.3	16.4	33.3
22	Hickman	38.5	31.7	30	21.6	19.8	15.1	38.9	48.9
23		27.8	47.4	19.3	13.1	27.7	4.4	46.8	53.5
24		24.7	44.6	16.1	23.7	20.7	6.2	41.6	41.5
25		26.1	51.8	15.4	21.5	33.1	9.8	52.1	51.9
26		18.6	48.6	10.1	22.3	28.2	4.8	47.2	44.3
27		30.9	37.8	22.4	25.4	16	7.5	35	45
28	Marshall	50.3	15.1	45.7	61.7	20.5	44.3	4.9	32
29		42	29.2	52.3	68.3	27.8	50.9	10.6	15.5
30	McCracken	24.7	56.3	25.2	57.6	31.6	40.1	37.6	11.3
31		28.5	40.9	24	56.6	17	39.2	21.9	9.8

Forest Residue									
No.	Biorefinery / Supply	Ballard	Calloway	Carlisle	Fulton	Graves	Hickman	Marshall	McCracken
32	Ballard	16.1	73.5	24.6	56.9	47.8	39.5	54.8	29.3
33		12.2	74	20.7	53.1	43.1	35.6	55.3	29.8
34		8.5	72.6	17.1	49.4	39.5	31.9	53.9	28.4
35		3.9	51.2	13.6	45.9	27.3	28.4	44.6	32.2
36	Calloway	67.9	15	63.4	66.2	33.5	54.6	19	43.1
37		62.5	10	57.9	61.2	31.8	55.2	26	54.3
38	Carlisle	9.6	45.5	7.9	40.2	21.6	22.7	38.9	29.2
39		16.2	55.4	7.6	29.2	26.6	11.7	45.7	41.9
40		7.9	55.9	6.1	38.5	32	21	49.3	39.6
41		14.8	44.2	8.8	38.4	20.3	20.9	37.6	31.5
42		11.9	53.9	3.4	32.8	30	18.3	47.3	37.6
43	Fulton	34.1	48.1	25.6	6.8	37.9	10.7	57	59.8
44	Graves	39.5	31.1	34.9	51	10.5	33.5	16	18.8
45		37.8	31.4	29.3	32.4	13.4	14.4	32.5	42.5
46		49.2	19.5	40.7	31.8	13.2	25.8	33.7	43.8
47	Hickman	23.6	48.6	15	21.1	28.2	5.3	47.3	49.3
48	Marshall	57.5	27.9	52.9	68.9	28.4	51.5	9.8	23.3
49		53.9	14.7	49.3	66.1	23.2	48.7	11.2	38
50	McCracken	35.7	32.3	31.1	60.1	19.6	42.7	15.1	9.9

Chicken Litter									
No.	Biorefinery / Supply	Ballard	Calloway	Carlisle	Fulton	Graves	Hickman	Marshall	McCracken
51	Ballard	3.2	58.1	11.8	44.1	34.2	26.6	51.5	30.5
52	Calloway	46	10.2	41.4	45.7	15.3	35.5	24	42.8
53		61.6	10.1	57	61.2	26.8	55.6	15.1	43.3
54	Carlisle	13.4	47	4.8	34.4	23.1	17	40.4	35.5
55	Fulton	47.4	55.9	38.8	5.8	43.4	23.9	62.4	72.5
56	Graves	21.1	35	16.6	49.5	11.1	24.9	28.5	23.7
57		25.6	33	21	48.8	9.1	31.4	25.7	21.8
58		39.8	26.6	35.2	52	9.1	34.6	15.5	24.1
59		29.6	29.7	23.5	37	6.1	19.8	25.2	35.2
60		36.6	34.2	28	26.6	14.5	13.2	33.6	43.6
61		42.2	27	36.8	28.4	13.3	21.9	32.3	42.3
62		46.2	25.2	37.7	28.8	18.5	22.8	39.1	49
63		51.8	18	43.3	34.3	15.9	28.4	33.3	43.3
64		48.6	16.3	48.2	39.3	18	33.3	35.4	45.4
65	Hickman	26.2	41	17.6	18.7	25.8	2.7	44.9	51.9
66		28.2	40.6	19.6	22.2	18.6	4.7	37.6	47.7
67		31.1	49.8	22.6	12.4	31	7.7	50.1	56.8
68		28.3	42.2	19.8	23.9	20.2	6.4	39.2	41.1
69		22.1	47.1	13.5	26.2	23.2	8.7	44.1	47.8
70		21.9	47.3	13.4	21	26.9	3.6	46	47.6
71	Marshall	54.4	19.4	49.8	65.8	25.3	48.4	5.4	32.7

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