

## **A Decision Support System (DSS) for Biomass-to-Biofuel Supply Chain**

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### **ABSTRACT**

In the recent years, due to the increase of our awareness about environmental issues and due to the increase of price of fuel, there has been a growing interest on biofuels. Research efforts have been concentrated on identifying efficient ways to manage the resources and the processes involved in converting biomass to biofuels. In this paper we present an Excel-based decision support system (DSS) to aid the process of designing and managing of the biomass-to-biofuel supply chain. These tools are very important because well managed supply chains have the potential to reduce the cost of biofuel. The DSS proposed identifies locations and capacities for biorefineries that minimize the total of transportation and inventory costs in the supply chain. We use this DSS to perform sensitivity analysis with respect biomass supply, facility locations, costs, etc.

### **INTRODUCTION**

The growing demand and price of energy, the limited availability of fossil fuels, and our increased awareness on environmental issues have been the reasons for the recent efforts in identifying sustainable sources of energy. A promising venue that is being explored by many researchers is the development of renewable fuels, such as biofuels. Technologies for producing corn-based and lignocellulosic-based ethanol are already being developed [1]. In 2010, 13 billion gallons (BGY) of ethanol were produced in the USA. As reported by the Renewable Fuels Association (RFA) [2], this amount of ethanol replaced an equivalent of 445 million barrels of gasoline. The Biofuels Security Act of 2007 signed by President Obama [3] mandates biofuels' production to reach 10 BGY mark by 2010, 30 BGY by 2020 and 60 BGY by 2030. In response to this Act, the office of Energy Efficiency and Renewable Energy initiated the Biomass Program. The goal of this program is initiating collaborations among industry, academia and national laboratories for undertaking research reforms to transform biomass resources into high performance and cost-competitive biofuels. A major challenge identified by the industry and academia for using biomass as a source of energy is the management of the logistics necessary to supply biomass to a biorefinery and distribute biofuels to markets. It is clear that a holistic approach should be taken when approaching this logistics and

supply chain management problem. All resources required for harvesting, storing, transporting and processing of biomass to biofuel should be considered.

The DSS that we propose takes into consideration a number of issues related to supplying biomass to a biorefinery. The DSS serves as a decision making tool for managers in the biofuel industry that helps with designing and managing efficient biomass-to-biofuel supply chains. This DSS is built in Excel. We use Visual Basic for Applications (VBA) to create a friendly user interface, and code the algorithms used to solve the supply chain-related problems.

The goal of the mathematical models that we use in the DSS is coordinating long-term supply chain design decisions with the mid-term supply chain management decisions. In particular, this DSS can (a) determine the location and size of biorefinery given the amount of biomass available and costs; (b) estimate the minimum biofuel delivery cost; and (c) perform sensitivity analysis with respect to changes in problem parameters, such as, biomass availability and costs.

DSS tools are used by decision-makers in a number of different sectors, such as, corporate management, government agencies, military, urban planning, natural resource allocation, etc. For an extensive review about DSS applications, the reader is referred to [4]. DSS tools are mainly used to manipulate quantitative models, access and analyze large data sets and support group decision making [5]. They are used to help decision-makers and not replace them [6]. A number of DSS tools have been developed in support of decision-making in the biofuel sector. For example, the Straw HAndling Model (SHAM) [7, 8], Integrated Biomass Supply Analysis and Logistics (IBSAL) model [9], and BIOmass LOGistics Computer Simulation (BIOLOGICS) [10]. These models provide a detailed description of the processes involved and the data required for estimating the cost of supplying biomass to a biorefinery. They employ sensitivity analyses to show how using different equipment, or harvesting and collection processes, impacts biomass supply costs. A major difference between these models and the one proposed in this paper is that there is a minimal to no consideration of the design aspect of the biomass-to-biofuel supply chain. Our model considers biomass supply and costs when designing and managing this supply chain. Our supply chain does not end at the biorefinery, we also consider the delivery of biofuels to the market. We use data from the State of Mississippi to validate the mathematical models, and validate the functionality of the DSS tool.

## PROBLEM DEFINITION

Figure 1 gives a network representation of the biomass-to-biofuel supply chain. This supply chain has 4 echelons that are harvesting sites (*HS*), collection facilities (*CF*), biorefineries (*BR*), and biofuel markets (*M*). The dashed boxes represent different time periods. Arrows indicate the direction of flow of either biomass or biofuel from one facility to another; and dashed arrows represent flow of biomass or biofuel inventory between the same facilities from a time period (*t*) to time period (*t + 1*).

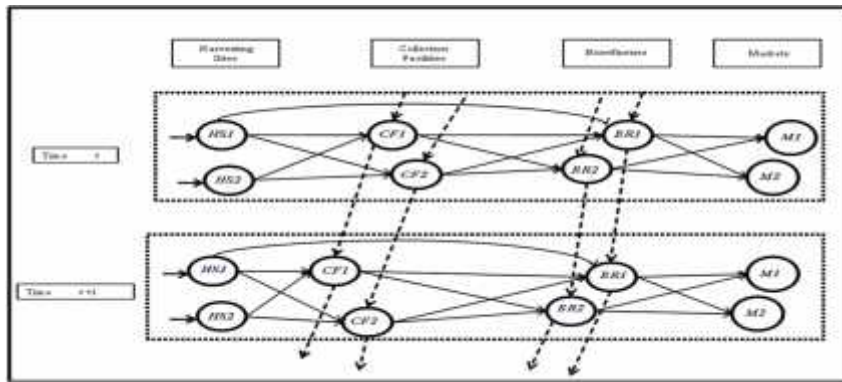


Figure 1 Biomass-to-Biofuel Supply Chain Network

Eksioglu *et al.* [11] modeled the problem as a mixed integer program (MIP). The objective of the MIP is to minimize the total costs (location, production, transportation and inventory) of flowing biomass and biofuels in this supply chain. The constraints of this problem are the flow conservation constraints, biomass availability and capacity constraints. This problem is solved to optimality using CPLEX 9.0 solver. The DSS presented here is based on the model developed by Eksioglu *et al.*

## DECISION SUPPORT SYSTEM

The development of this DSS was guided and motivated from discussions we had with business experts in the biomass and biofuel industries in Mississippi. Investors in the biofuel industry have identified facility size and location to be the two most important factors when making their decisions. This is mainly due to two facts. First, investment costs for a biorefinery are very high. For example, a 100MGY cellulosic ethanol plant costs somewhere between \$400 to \$500 million [12]. Second, the production of biofuels is greatly dependent on the availability of biomass. Therefore, an investor is very interested to know the costs that he will incur for a particular facility size located in a location he has identified. Investors, however, are open to examining other sizes and locations to identify the best investment opportunity. Figure 2 presents a schematic of the different problems we investigate in this DSS.

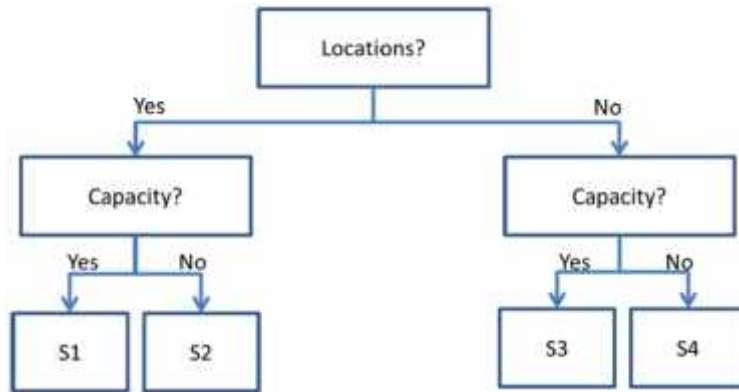


Figure 2 Biomass-to-Biofuel Supply Chain Problem Definitions

We solve problem S1 when an investor knows exactly facility location and size and needs to know what biofuel delivery costs to expect. S1 is a transportation problem [13]. In this problem, we are given biomass supply points, biorefinery location and size, biofuel markets and related costs. We identify facility assignments that minimize total costs in the supply chain.

Problem S2 is a capacity allocation and transportation problem. In our model we consider only a set of typical production capacities. We have designed an algorithm which solves problem S1 for each production capacity. The capacity that results on minimum supply chain costs is then identified. Note that, an increase in production capacity impacts not only investment costs, but also transportation costs. This is due to the fact that, to secure the amount of biomass needed, a facility will receive shipments from farms located further away.

Problem S3 is a facility location problem. In this problem we identify the location for a facility of a given capacity in such a way that the total supply chain costs are minimized. Problem S4 is a capacitated facility location problem where we need to determine the locations as well as sizes for the facilities based on the biomass supply, biofuel demand, and related costs.

The problems addressed by this DSS are special cases of the Facility Location Problem (FLP) and Capacitated Facility Location Problem (CFLP). The literature provides algorithms for solving these problems, such as, LP-Rounding [14, 15], Local Search [16, 17], Greedy Heuristics [18, 19] etc. We designed our algorithms based on a simple local search and greedy heuristic approach similar to the weighted gravity method described by Nahmias [20].

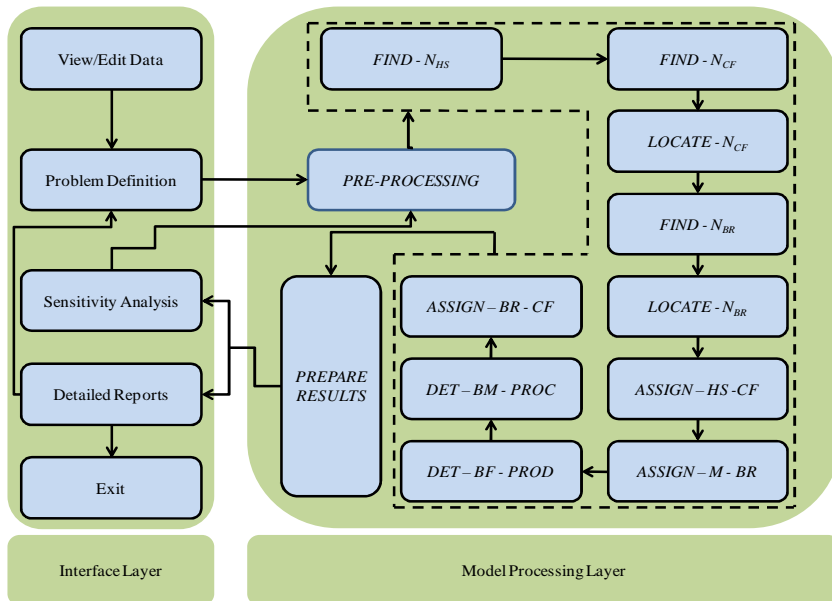


Figure 3 DSS Workflow

Figure 3 represents the DSS workflow. The interface layer presents all the forms we have designed to facilitate the interaction of a user with the system. The model processing layer presents the algorithms designed to solve problems S1 to S4. The interface layer enables the user to view and edit input data, and define the problem of interest. User’s input is used to pre-process the data, that is, identify the amount of biomass needed considering biomass types available and corresponding conversion rates, and make sure that demand doesn’t exceed supply (to maintain problem feasibility). This information is used in the model processing layer to identify the number of harvesting sites ( $FIND-N_{HS}$ ), find the number ( $FIND-N_{CF}$ ,  $FIND-N_{BR}$ ) and location ( $LOCATE-N_{CF}$ ,  $LOCATE-N_{BR}$ ) of collection facilities and biorefineries. Finally, we use an assignment algorithm to identify the best facility assignments ( $ASSIGN-HS-CF$ ,  $ASSIGN-BR-CF$ ,  $ASSIGN-M-BR$ ), and determine the corresponding costs related to biofuel (BF) production ( $DET-BF-PROD$ ) and biomass (BM) processed ( $DET-BM-PROC$ ). The user is provided with the options of (a) viewing a report that gives detailed supply chain related costs; (b) performing sensitivity analysis with respect to biomass availability and costs; (c) redefining and solving a new problem.

## COMPUTATIONAL RESULTS

We use the state of Mississippi as a testing ground for the algorithms developed and the DSS created. The DSS can identify supply chain related costs for different biomass types, however, in this case study we only consider one type of biomass (corn) producing one type of biofuel (ethanol) mainly due to the availability of data. Each county in Mississippi is considered a potential harvesting site and collection

facility location. Data about corn availability at the county level is provided by United States Department of Agriculture’s (USDA) National Agricultural Statistics Service (NASS) web-site [21]. Twenty-five counties are selected as potential biorefinery locations. Proposed biorefinery capacities and corresponding investment cost are identified from discussions with experts and practitioners in the biofuel industry, and from a report by Wallace *et al.* [22]. Capacities and investment costs for collection facilities are based on the article by Dagher and Robbins [23]. Potential biorefineries and collection facilities capacities and investment costs are presented in Table 1. Seven major Mississippi cities were chosen as potential demand points and their demands are calculated based on the “2006 State by State Ethanol Handbook” published by American Coalition for Ethanol (ACE) [24].

Table 1 *BR* and *CF* Capacities and Investment Costs

<i>BR</i> Capacity (MGY)	<i>BR</i> Investment Cost (\$ Millions)	<i>CF</i> Capacity (dry tons/year)	<i>CF</i> Investment Cost (\$ Millions)
10	18.30	56,006	0.80
20	27.70	112,013	1.60
30	35.40	140,016	2.00
40	42.10	-	-
60	53.60	-	-
100	70.67	-	-
150	86.97	-	-

In order to test the validity of the algorithms we developed for solving problems S1 to S4, we compare the results from these algorithms with the solutions found from CPLEX when solving the corresponding MIP formulation. Table 2 summarizes these results. For this purpose, we have generated and solved a total of 175 instances of problem S1, one for each pair of facility size and location (25 locations and 7 sizes). We solved 25 instances of problem S2, one problem for each potential facility locations. We solved 7 instances of problem S3, one for each potential facility sizes. Finally, we solved 5 instances of problem S4, considering different levels of demand for ethanol. We started with a base-case ethanol demand level, and next changed demand by  $\pm 10\%$  and  $\pm 20\%$ . The CPU time required by CPLEX and DSS for solving different instances of problem S1 is presented in Figure 4.

Table 2 Percentage Gap for DSS-CPLEX solutions

Problem		GAP (%)			
		S1	S2	S3	S4
DSS-CPLEX	<b>Min</b>	1.13	0.13	0.03	3.32
	<b>Average</b>	5.60	3.91	2.99	6.26

	<b>Max</b>	14.99	7.39	8.74	9.81
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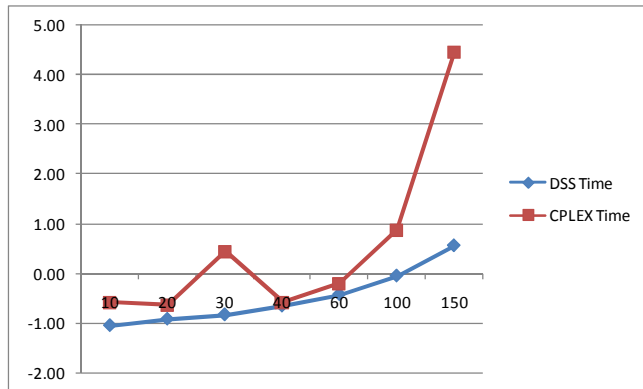


Figure 4 CPU Times for solving instances of problem S1

Due to the large difference between the CPU times taken by DSS and CPLEX, the CPU times are represented using a logarithmic scale. It is clear from the figure that the time taken by CPLEX increases exponentially as compared to time taken by DSS. For one problem instance, CPLEX went out of memory and was unable to solve the problem, whereas the DSS solved the same problem in 2.80 seconds.

The results of Table 2 indicate that the quality of solutions from the DSS is comparable with CPLEX. In certain problem instances CPLEX is superior. However, we should be mindful that the purpose of proposing this DSS is to provide the users with a friendly tool, which will provide a quality solution every time you run the model, and provide a solution within a reasonable amount of time.

Table 3 presents summary of results for problem S4. The minimum optimality gap obtained for these problems is 3.32% and maximum is 9.81%. This gap depends on the facility size and demand for ethanol selected. The facility locations chosen by DSS are similar to that chosen by CPLEX. For example, CPLEX selects Sunflower and Yazoo counties as facility locations for instance 2 (demand = 151,200,000 gallons) of problem S4, whereas DSS selects Sunflower and Holmes counties for the same. Both Yazoo and Holmes counties are adjacent to each other and their distance is minimal.

Table 3 Summary of Results for Problem S4

Ethanol Demands		Problem S4				
		GAP (%)	DSS		CPLEX	
			BR	Capacity	BR	Capacity
134,400,000	(-20%)	3.32%	Sunflower	150	Sunflower	100
					Yazoo	40

151,200,000	(-10%)	5.36%	Sunflower	150	Sunflower	100
			Holmes	10	Yazoo	60
168,000,000	(+0%)	6.43%	Holmes	150	Hinds	30
			Sunflower	20	Sunflower	100
					Yazoo	40
184,800,000	(+10%)	6.37%	Holmes	150	Hinds	40
			Sunflower	30		
			Montgomery	10	Sunflower	150
201,600,000	(+20%)	9.81%	Montgomery	150	Lafayette	60
					Sunflower	60
			Holmes	60	Yazoo	100

Figure 5 presents the solution values for all the instances of problem S1 as obtained by DSS and CPLEX. The solution values present the total unit cost of delivering ethanol to the market. Note that, although there is a gap between the solution values found by CPLEX and DSS, there is a similar trend followed by both methods. An observation of interest is that, both methods suggest 40MGY to be the optimal ethanol production facility size in MS provided the amount of corn in the state and related costs. It is understandable that, as the facility size increases, the unit cost decreases due to economies of scale. However, facilities of a size larger than 40MGY are not necessary more economical, despite the economies of scale on ethanol production. The reason behind this fact is that MS is a corn deficit state. There is a limit on how much corn is available in MS for production of ethanol. Larger facilities will have to ship corn from neighbouring states, or from the Midwest. As a result the delivery cost of ethanol will increase due to higher biomass (corn) transportation costs.

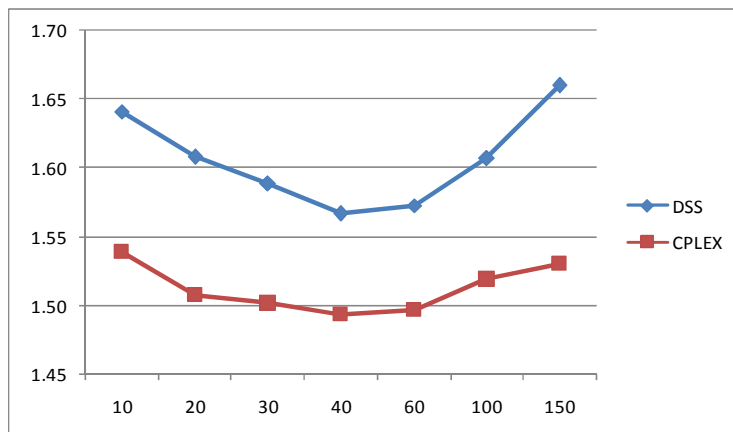


Figure 5 Solution values (\$/gal) for instances of problem S1



## CONCLUSION

This paper proposes an Excel-based DSS to design and manage the biomass-to-biofuel supply chain. We validate the quality of algorithms we develop for the DSS by comparing the solutions obtained with CPLEX. The average gap for all problem types ranges from 2.5-6.5%. We identify problem instances for which CPLEX went out of memory without providing a feasible solution. DSS provides quality solutions for all problem instances in a short time.

The ease of using this Excel-based DSS due to its user-friendly interface is another advantage over CPLEX. As a result, investors and other decision-makers in the biofuel industry can easily use this tool to get insights on how biomass availability and supply chain related costs impact the delivery cost of ethanol.

## REFERENCES

- [1] Aden, A., M. Ruth, K. Ibsen, J. Jechura, K. Neeves, J. Sheehan, B. Wallace, L. Montague, A. Slayton, and J. Lukas, (2002) *Lignocellulosic Biomass to Ethanol Process Design and Economics Utilizing Co-Current Dilute Acid Prehydrolysis and Enzymatic Hydrolysis for Corn Stover*, National Renewable Energy Laboratory.
- [2] RFA, (2010) *2010 Ethanol Industry Outlook: Building Bridges to a More Sustainable Future*, Renewable Fuels Association.
- [3] Harkin, T., Lugar, Dorgan, J. Biden, and B. Obama, (2007) *Biofuels Security Act of 2007*, Senate and House of Representatives of the United States of America in Congress Assembled: Washington, DC.
- [4] Eom, S.B., S.M. Lee, C. Somarajan, and E.B. Kim (1997) *Decision Support Systems Applications - A Bibliography (1988 - 1994)*. OR Insight, **10** (2), 18-32.
- [5] Eom, S.B., S.M. Lee, E.B. Kim, and C. Somarajan (1998) *A Survey of Decision Support System Applications (1988-1994)*. The Journal of the Operational Research Society, **49** (2), 109-120.
- [6] Alter, S. (1980) *Decision Support Systems : Current Practice And Continuing Challenges*. Addison-Wesley Pub., Co., Reading, MA.
- [7] Nilsson, D. (1999) *SHAM--a simulation model for designing straw fuel delivery systems. Part 1: model description*. Biomass and Bioenergy, **16** (1), 25-38.
- [8] Nilsson, D. (1999) *SHAM--a simulation model for designing straw fuel delivery systems. Part 2: model applications*. Biomass and Bioenergy, **16** (1), 39-50.
- [9] Sokhansanj, S., A. Kumar, and A.F. Turhollow (2006) *Development and implementation of integrated biomass supply analysis and logistics model (IBSAL)*. Biomass and Bioenergy, **30** (10), 838-847.

- [10] Mol, R.M.d., M.A.H. Jogems, P.V. Beek, and J.K. Gigler (1997) *Simulation and optimization of the logistics of biomass fuel collection*.
- [11] Eksioglu, S.D., A. Acharya, L.E. Leightley, and S. Arora (2009) *Analyzing the design and management of biomass-to-biorefinery supply chain*. Computers & Industrial Engineering, **57** (4), 1342-1352.
- [12] Lane, J. (2008) *Coskata, US Sugar in final negotiations over \$400 million, 100 Mgy cellulosic ethanol plant in Florida*. Biofuels Digest **Volume**,
- [13] Winston, W.L. (2004) *Operations Research Applications and Algorithms*. Thomson.
- [14] Lin, J.H. and J.S. Vitter (1992) *Approximate algorithms for geometric median problems*. Information Processing Letters, **44**, 245-249.
- [15] Shmoys, D.B., E. Tardos, and K. Aardal, (1997) *Approximation algorithms for facility location problems (extended abstract)*, in *Proceedings of the twenty-ninth annual ACM symposium on Theory of computing*, ACM: El Paso, Texas, United States.
- [16] Arya, V., N. Garg, R. Khandekar, A. Meyerson, K. Munagala, and V. Pandit, (2001) *Local search heuristic for k-median and facility location problems*, in *Proceedings of the thirty-third annual ACM symposium on Theory of computing*, ACM: Hersonissos, Greece.
- [17] Kuehn, A.A. and M.J. Hamburger (1963) *A Heuristic Program For Locating Warehouses*. Management Science, **9** (4), 643-666.
- [18] Jain, K., M. Mahdian, and A. Saberi, (2002) *A new greedy approach for facility location problems*, in *Proceedings of the thirty-fourth annual ACM symposium on Theory of computing*, ACM: Montreal, Quebec, Canada.
- [19] Mahdian, M., Y. Ye, and J. Zhang (2002) *Improved Approximation Algorithms for Metric Facility Location Problems*. Lecture Notes in Computer Science, **2462**, 229-242.
- [20] Nahmias, S. (1997) *Production And Operations Analysis*. Irwin.
- [21] NASS, (2007) *NASS Quick Stats*, USDA - NASS.
- [22] Wallace, R., K. Ibsen, A. McAloon, and W. Yee, (2005) *Feasibility study for co-locating and integrating ethanol production plants from corn starch and lignocellulosic feedstocks*.
- [23] Dagher, M.A. and L.W. Robbins (1987) *Grain export elevators: An economies of size analysis*. Agribusiness, **3** (2), 169-178.
- [24] ACE, (2006) *ACE State By State Ethanol Handbook*, American Coalition for Ethanol (ACE).