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Selecting Suppliers for Biomass Supply Networks with an IFS - Multi Periodic Optimization Method

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Abstract

The biomass supplier selection problem is characterized by a high degree of uncertainty because of subjective preferences/evaluations of decision makers, raw material cost fluctuations, variations in biomass seasonality and the dynamics of biomass demand. Designing a biomass supply chain often becomes a time-dependent problem that should be addressed by examining adequate supply schemes in different periods of time. This paper suggests the effectiveness of a multi-criteria decision making approach for systematically assessing uncertain biomass supplier profiles based on Intuitionistic Fuzzy Sets (IFS) in conjunction with a multi-periodic optimization framework for selecting the best biomass supply mix at a maximum total purchasing value.

Keywords
Supplier selection, Biomass supply networks, Intuitionistic fuzzy sets, Linear programming, Multi-periodic optimization

1. Introduction
A systematic decision-making approach can provide a lot of support in outsourcing biomass supply operations for bioenergy production (Frombo et al. 2009). So far, there is a low degree of strategic and operational integration between biomass suppliers and buyers, mainly due to the complexity of this kind of supply chains, compared to the traditional ones, and the existence of binding requirements for joint efforts from all relevant stakeholders, such as government organizations, industries, parties from the agricultural sector and consumer organizations. A biomass supply system presents several unique features that highly influence the bioenergy production and requires special technical and managerial knowledge (Van Dyken et al. 2010). Decision making on outsourcing biomass supply activities needs to take into account the complexity of their characteristics, such as: i) the dynamics of the demand, ii) biomass-specific features, such as time dependent availability (e.g., seasonality, yield) in terms of biomass quantities and types, iii) the disperse nature of the supply chain's locations, and iv) certain biomass properties (e.g., moisture, bulk density, energy density, energy yield etc.) which are important for the supply network functionality. One way to deal with the seasonality of the biomass supply requirements and achieve cost-effective supply utilization is via procurement from different suppliers (Min and Zhou 2002; Toka et al. 2010). However, any biomass supply schemes should be evaluated by bio-energy producers to ensure that biomass/biofuels supply chains are profitable, competitive and viable. Thus, any decision on strategic outsourcing of biomass supply chain activities needs to be carefully made, due to the special characteristics of the biomass supply network.

This paper emphasizes on the need for systematically selecting an appropriate combination of supply alternatives featuring optimal biomass supplier profiles in order to maximize the total benefits for the whole supply chain and minimize the associated production and logistics costs. Such a selection requires considering variations in the availability of various biomass types throughout a time horizon, as well as time fluctuations in their cost. Designing a biomass supply chain becomes a time-dependent problem and can be addressed by examining and developing the adequate supply schemes in different periods of time. In addition, the biomass supplier selection problem is characterized by a high degree of uncertainty because of subjective preferences/evaluations of the decision makers, unexpected demand variations and variable raw material prices, fluctuations in biomass availability in time and variations in the procurement lead times for each supplier. To meet these challenges, the paper suggests the use of Intuitionistic Fuzzy Sets - IFS (Atanassov 1986). IFS can be applied to handle, not only the uncertainty of decision makers to quantify biomass supplier selection criteria and suppliers' performances, but also to handle decision makers' likes and dislikes which need not to be complementary (Boran et al. 2009; Ye 2010). An IFS includes the membership and the non-membership function of an element to a conventional fuzzy set, as well as a third function that is called the hesitation degree. This third function is useful to express lack of knowledge and hesitancy concerning both membership and non-membership of an element to a set. Expression of hesitation is particularly helpful for decision makers when they need to select a proper combination of suppliers in a highly uncertain supply network such as a biomass supply system (Wu 2008). An IFS-based method (Li 2005) can be applied to derive biomass suppliers' ratings, for each considered time period. The output of the method can be further utilized by a linear programming optimization model to determine the combination of suppliers in different periods of the considered time horizon.

The paper is organized as follows. Section 2 presents the most important selection criteria for suppliers in a biomass supply system. Section 3 presents a brief review on fuzzy-based approaches in supplier selection problems and some introductory concepts relevant with IFS. In Section 4, the steps of the proposed method are described along with an application example. Conclusions and future research are given in Section 5.

2. Biomass Supply Chain Management Considerations and Supplier Selection Criteria

Many researchers have addressed the problem of planning, simulating and optimizing biomass supply chain activities, including collection, storage, pretreatment and transportation of primary resources (Fiala 2005; Gigler et al. 2002; Kazantzi et al. 2011). Based on the literature findings (Kazantzi et al. 2012), seven broad categories of selection/evaluation criteria of biomass suppliers can be identified. These categories include in total 11 criteria (Table 1).

Table 1: Criteria categories, definitions and associated symbols

Category	Criteria	Definition	Symbol
Reliability	Adherance to contract terms	The performance of a supplier in satisfying all requirements described as terms in the contract	X_1
	On-time orders / agreed quality and conditions of the orders	The performance of a supplier in delivering the ordered material to the right place, upon time, at the required conditions and quantity	X_2
Responsiveness	Lead time	The average actual required time from the moment the supplier receives an order to the moment it ships	X_3
	Return product velocity	Average time required for process of returning the defective orders and reshipping the order to customer	X_4
Flexibility	Flexible functionality / Revise order	Agility of supplier in responding to demand changes / ability to offer product variety	X_5
Cost / Financial aspects	Total cost / Total discount cost	Including component production/pretreatment cost, shipment cost, order cost, etc.	X_6
	Payment terms	Suitability of terms and conditions regarding payment of invoices, open accounts, sight drafts, credit letter and payment schedule	X_7
Quality	Quality characteristics	Quality aspects (defect rates, biomass properties, such as moisture, density etc.)	X_8
	Quality System Certification	Quality certifications acquired	X_9
Assets / Infrastructure	Company's location, size and infrastructure	Including location (proximity to customer), transportation infrastructure, facility size, fleet size, warehouse number and capacity etc.	X_{10}
Environment / Safety	Environmentally conscious aspects / Safety conditions	Environmentally conscious biomass production and handling, safety conditions at field and in handling/transporting material	X_{11}

3. Fuzzy-based Approaches and Intuitionistic Fuzzy Sets in Supplier Selection Problems

Fuzzy-based approaches may be used to cope with uncertainties in supplier selection problems which involve a dynamically changing supply market with high degree of uncertainties regarding mainly qualitative factors. There are two broad categories of fuzzy-based supplier selection methods (Vahdani and Zandieh 2010). In the first category, there are techniques, which imprecisely represent weights of selection criteria and performances of suppliers with fuzzy numbers. In the second category, there are methods, which make use of linguistic terms to evaluate criteria and suppliers. In the literature, there are also hybrid fuzzy-based approaches, which combine fuzzy techniques with the Analytic Hierarchy Process - AHP (Chan et al. 2008) or the Technique for Order Performance by Similarity to Ideal Solution - TOPSIS (Wang et al. 2009). Finally, some extensions of fuzzy sets have been proven valuable to deal specifically with uncertainties in complex supplier selection settings. Such an extension is Intuitionistic Fuzzy Sets (IFS) which allow decision makers to express also their hesitation degree or ambiguity when they evaluate the performance of alternative suppliers and determine the importance of the selection criteria. Representative examples of IFS applications in supplier selection problems can be found in (Boran et al. 2009; Ye 2010). Before proceeding to describe the steps of the proposed biomass supplier selection method, some necessary introductory concepts of Intuitionistic Fuzzy Sets (IFS) need to be briefly introduced. An IFS, *I* in a finite set, *E* can be defined as (Atanassov 1986):

$$I = \{< x, \mu_I(x), v_I(x) > | \, x \in E\} \tag{1}$$

where $\mu_I : E \to [0,1]$, $v_I : E \to [0,1]$ and $0 \le \mu_I(x) + v_I(x) \le 1 \quad \forall x \in E \quad \mu_I(x)$ and $v_I(x)$ denote respectively the degree of membership and non-membership of *x* to *E*.

For each IFS, *I* in *E*, $\pi_I(x) = 1 - \mu_I(x) - v_I(x)$ is called the hesitation degree of whether *x* belongs to *I*. If the hesitation degree is small, then knowledge whether *x* belongs to *I* is more certain, while if it is great, then knowledge on that is more uncertain. Thus, an ordinary fuzzy set can be written as:

$$\{< x, \mu_I(x), 1 - \mu_I(x) > | \, x \in E\} \tag{2}$$

The next section of the paper presents the steps of a practical and risk-informed decision making approach for estimating, rating and optimizing the biomass supplier profiles with respect to time in a multi sourcing dynamic environment. The suggested approach involves multi decision makers in a group decision making setting and adopts a method from multi-attribute utility theory that has been presented in (Li 2005) and applied also in other application domains (Hernadez and Uddameri 2010). This approach is a hybrid method that combines IFS with linear programming to find optimal weights for the evaluation/selection criteria. A comparison index similar to the one suggested by TOPSIS (Hwang and Yoon 1981) was used for determining the ratings of the biomass suppliers. The adopted approach is further extended in this paper by utilizing the ratings of the suppliers as inputs to a linear, multi-period optimization model that aims to determine an appropriate combination of suppliers with their respective optimal types and amounts of biomass supplies in different time periods.

4. Steps of the Selection Method

Suppose that there is a set of candidate biomass suppliers $S = \{S_1, S_2, ..., S_n\}$. Each supplier is evaluated on *m* selection/evaluation criteria, i.e., the set of criteria is denoted by $X = \{X_1, X_2, ..., X_m\}$. There is also a group of *k* decision makers responsible to evaluate the suppliers' performances with respect to each criterion.

4.1 Step 1: Evaluate the Performance of Biomass Suppliers on the Selection Criteria

In the first step of the approach, the values of μ_{ij} , v_{ij} and π_{ij} , which define the degree of membership, non-membership and the hesitation of each supplier $S_j \in S$ respectively, regarding each criterion $X_i \in X$ are calculated, according to the fuzzy concept of "appropriateness". These values can be determined by asking all *k* decision makers to express their opinion whether each supplier S_j is appropriate or not with respect to an evaluation criterion X_i . Suppose that from the *k* decision makers, *k1* answered that S_j is appropriate to fulfill criterion X_i (i.e., *k1* decision makers expressed a positive opinion for the supplier with respect to the criterion), *k2* answered that S_j is not appropriate to fulfill criterion X_i (i.e., *k2* decision makers expressed a negative opinion for the supplier with respect to the criterion) and *k3* gave no answer due to their lack of knowledge/ indeterminacy about the appropriateness of S_j with respect to criterion X_i (it should be noted that *k*= *k1*+*k2*+*k3*). Then the values of μ_{ij} , v_{ij} and π_{ij} are calculated as follows:

$$\mu_{ij} = k_1 / k \,, \; v_{ij} = k_2 / k \;\; \text{and} \; \pi_{ij} = k_3 / k \tag{3}$$

Given the indeterminacy of decisions makers, a certain hesitation in the degree of membership μ_{ij} that is denoted by lower μ^l_{ij} and upper μ^u_{ij} bounds, exists and it is expressed as follows:

$$\mu^l_{ij} = \mu_{ij} \;\; \text{and} \;\; \mu^u_{ij} = \mu_{ij} + \pi_{ij} = 1 - v_{ij} \tag{4}$$

The upper bounds of memberships are useful to consider the case that decision makers overcome their hesitation in favor of the suppliers. Consider, for example, that three candidate suppliers, S_1, S_2 and S_3, have been identified to supply biodiesel producers with certain feedstock types; supplier S_1 can provide rapeseed (RP), supplier S_2 can provide both rapeseed (RP) and sunflower (SN) and supplier S_3 can deliver waste cooking oil (WCO). Suppose that 11 evaluation criteria (X_1, X_2,…, X_{11}) are considered (Table 1). Let us also suppose that there are 10 (*k*=10) decision makers, who evaluate the alternative suppliers with respect to the determined criteria. Their collective evaluations (based on equation (3)) are presented in Table 2. Note in Table 2 that, for example, 4 out of 10 decision makers evaluated that the supplier S_1 supports appropriately criterion X_1 (i.e., the membership value is equal to 0.4), 5 out of 10 decision makers evaluated that the supplier S_1 is not appropriate with respect to criterion X_1 (i.e., the non-membership value is equal to 0.5) and one decision maker was hesitant upon the performance of supplier S_1 with respect to criterion X_1 (i.e., the hesitation degree is equal to 0.1). Table 3 presents the lower/upper bounds for the evaluation of each supplier, in the case in which all decision makers insist on overcoming their hesitation. For example, consider that the appropriateness of the supplier S_1 upon criterion X_1 can have a value between 0.4 (lower bound) and 0.5 (upper bound).

Table 2: Evaluation of suppliers with respect to criteria

	S_1		S_2		S_3	
	μ_{ij}	v_{ij}	μ_{ij}	v_{ij}	μ_{ij}	v_{ij}
X_1	0.4	0.5	0.7	0.2	0.9	0.1
X_2	0.4	0.5	0.4	0.5	0.5	0.4
X_3	0.1	0.9	0.8	0.1	0.9	0.1
X_4	0.4	0.5	0.5	0.4	0.4	0.5
X_5	0.1	0.8	0.9	0.1	0.5	0.4
X_6	0.6	0.4	0.1	0.9	0.8	0.1
X_7	0.7	0.2	0.1	0.9	0.5	0.4
X_8	0.8	0.1	0.5	0.4	0.1	0.9
X_9	0.9	0.1	0.5	0.4	0.1	0.9
X_{10}	0.4	0.5	0.9	0.1	0.5	0.4
X_{11}	0.4	0.5	0.4	0.5	0.7	0.2

4.2 Step 2: Specify weights for the selection criteria

In the second step, the weights for the selection criteria are specified. We suppose that this task is a responsibility of the director of the supply chain that is the person responsible for the overall management of the supply chain. The director applies a “Hundred-Dollar Test”-like prioritization method to subjectively allocate $100 dollars (or €100 Euros) to the selection criteria (i.e., this method is also known as Cumulative Voting (Leffingwell and Widrig 2003) and it was proposed in the software engineering domain for prioritizing software requirements). The amount of “money” assigned to each supplier selection criterion represents its relative weight in relation to the other criteria. An amount of $100 dollars can be distributed in any way that represents the preferences of the director to the criteria. It is also possible some amount of money to be not distributed to any of the criteria. To take into account indeterminacy, the director may also specify how many additional dollars can be possibly given to each criterion. In this way, the degree of membership ρ_i and the degree of hesitancy n_i of each criterion X_i to the fuzzy concept of "importance" are specified. Thus, the weight ω_i of each criterion X_i is a number that lies within the interval $[\omega_i^l, \omega_i^u]$, where:

$$\omega_i^l = \rho_i,\ \omega_i^u = \rho_i + n_i,\ 0 \le \omega_i^l \le \omega_i^u \le 1,\ \sum_{i=1}^{m} \omega_i^l \le 1 \text{ and } \sum_{i=1}^{m} \omega_i^u \ge 1 \tag{5}$$

The first two columns of Table 4 present lower and upper bounds of the weights of the criteria in the numerical example. For example, the weight of criterion X_1 is between 0.15 (lower bound) and 0.3 (lower bound). These values have been realized as follows: 0.15 denotes that 15 dollars were allocated to X_1, while this value can be increased up to 0.3 (upper bound) by considering an additional amount of money equal to 15 dollars (i.e., the hesitation degree is equal to 0.15). Values of weights which are less than 0.1 correspond to allocating only cents to criteria, denoting low values in the criteria weights.

Table 3: Lower and upper bounds for the evaluation of suppliers with respect to criteria

	S_1		S_2		S_3	
	μ_{ij}^l	μ_{ij}^u	μ_{ij}^l	μ_{ij}^u	μ_{ij}^l	μ_{ij}^u
X_1	0.4	0.5	0.7	0.8	0.9	0.9
X_2	0.4	0.5	0.4	0.5	0.5	0.6
X_3	0.1	0.1	0.8	0.9	0.9	0.9
X_4	0.4	0.5	0.5	0.6	0.4	0.5
X_5	0.1	0.2	0.9	0.9	0.5	0.6
X_6	0.6	0.6	0.1	0.1	0.8	0.9
X_7	0.7	0.8	0.1	0.1	0.5	0.6
X_8	0.8	0.9	0.5	0.6	0.1	0.1
X_9	0.9	0.9	0.5	0.6	0.1	0.1
X_{10}	0.4	0.5	0.9	0.9	0.5	0.6
X_{11}	0.4	0.5	0.4	0.5	0.7	0.8

Table 4: Lower and upper bounds of criteria weights and optimal criteria weights

	ω_i^l	ω_i^u	ω_i
X_1	0.15	0.3	0.191
X_2	0.18	0.2	0.2
X_3	0.1	0.2	0.1
X_4	0.01	0.05	0.05
X_5	0.08	0.1	0.084
X_6	0.13	0.25	0.13
X_7	0.03	0.05	0.034
X_8	0.1	0.1	0.1
X_9	0.02	0.05	0.02
X_{10}	0.05	0.05	0.05
X_{11}	0.04	0.05	0.04

4.3 Step 3: Determination of optimal weights for the selection criteria

By adopting the approach presented in (Li 2005), an optimal set of weights is determined for the criteria that can be used to calculate the weighted average rating (score) z_j for each supplier S_j. A linear optimization model can be solved to determine optimal weights of the criteria:

$$\max\left\{\frac{\sum_{j=1}^{n}\sum_{i=1}^{m}(\mu_{ij}^{u}-\mu_{ij}^{l})\omega_i}{n}\right\} \tag{6}$$

Subject to: $\omega_i^l \le \omega_i \le \omega_i^u \;\; \forall i=1,\dots,m$, $\sum_{i=1}^{m}\omega_i = 1$

The final column in Table 4 shows the optimal weights of criteria computed by solving the above linear programming optimization model for the example case, while the maximum weighted average rating (max(z_j)) is calculated to be equal to 0.196.

4.4 Step 4: Computation of supplier ratings

By utilizing the optimal criteria weights, the lower (z_j^l) and upper (z_j^u) bounds of the weighted rating (scores) z_j for each supplier S_j can be computed (Li 2005):

$$z_j^l = \sum_{i=1}^{m}\mu_{ij}^{l}\omega_i = \sum_{i=1}^{m}\mu_{ij}\omega_i \;\; \forall j=1,\dots,n \tag{7}$$

$$z_j^u = \sum_{i=1}^{m}\mu_{ij}^{u}\omega_i = 1-\sum_{i=1}^{m}v_{ij}\omega_i \;\; \forall j=1,\dots,n \tag{8}$$

Table 5 presents the lower and upper bounds for each supplier weighted score calculated by applying equations (7) and (8). To obtain the final ranking of each supplier S_j, a comparison index ξ_j based on the TOPSIS method can be used (Li 2005; Hwang and Yoon 1981):

$$\xi_j = \frac{D(A_j^0, B)}{D(A_j^0, B) + D(A_j^0, G)} \tag{9}$$

In equation (9), A_j^0 is the IFS that represents the optimal ranking value of the supplier S_j, G is the IFS that corresponds to the ideal alternative supplier and B is the IFS that corresponds to the negative ideal supplier:

$$A_j^0 = \{< S_j, z_j^l, 1-z_j^u >\} = \{< S_j, \sum_{i=1}^{m}\mu_{ij}\omega_i, \sum_{i=1}^{m}v_{ij}\omega_i \tag{10}$$

$$G = \{< g,1,0 >\} \text{ and } B = \{< b,0,1 >\} \tag{11}$$

In equation (9), D stands for the Hamming Distance measure for IFS (Szmidt and Kacprzyk 2000). By calculating the distances, the comparison index ξ_j of a supplier S_j can be defined as follows:

$$\xi_j = \frac{z_j^u}{1+z_j^u-z_j^l} \tag{12}$$

The alternative suppliers can be ranked in an increasing order of their comparison index and the most appropriate supplier is the one with the highest comparison index. In the numerical example, the comparison indices for suppliers are listed in Table 6. These comparison indices are normalized in the interval [0..1] and final ratings are listed in parentheses in Table 6. The best supplier is S_3, while the ranking of the three suppliers is $S_3 \succ S_2 \succ S_1$.

4.5 Step 5: Total Purchasing Value and Order Allocation Optimization

The next step for addressing the biomass supplier selection problem is to answer the following questions:

- Which supplier(s) should be chosen based on the previously derived evaluation ratings?
- When?

- What type of biomass feedstock should be supplied by each selected supplier and how much feedstock will be supplied by each selected supplier?
- How would total budget for the biomass purchasing function be allocated?
- What would be the maximum total purchasing value in each time period considered?

Table 5: Lower and upper bounds of weighted ratings for suppliers

S_1		S_2		S_3	
z_1^l	z_1^u	z_2^l	z_2^u	z_3^l	z_3^u
0.431	0.506	0.532	0.634	0.610	0.714

Table 6: Comparison indices for suppliers

ξ_1	ξ_2	ξ_3
0.471 (0.278)	0.576 (0.340)	0.647 (0.382)

Table 7: Total ratings for each supply alternative per time period (monthly basis)

Supplier		S_1	S_2	S_3
Month		$w_{t,i}$		
January	1	0.301	0.374	0.325
February	2	0.291	0.350	0.358
March	3	0.278	0.340	0.382
…	…	…	…	…
December	12	0.280	0.350	0.370

Table 8: Data on suppliers' capacity per month

Month		Capacity (tn/mo)			
		S_1	S_2 for *b1*	S_2 for *b2*	S_3
January	1	350	300	400	100
February	2	450	300	450	150
March	3	350	200	400	150
….	…	….	…	….	…
December	12	300	200	250	350

Table 9: Purchasing costs for each supply alternative, total demand and purchasing budget

Cost (€/tn)				Total Budget (€)	Total Demand (tn/mo)
S_1	S_2 for *b1*	S_2 for *b2*	S_3		
5.5	8	8	6.5	9000	1000

A decision-making time horizon H needs to be determined. Within this horizon, the variations in the market conditions are anticipated and expressed in terms of time-dependent changes in biomass quantities, available types and prices of supply, as well as demand. The decision-making time horizon H is discretised into N_t periods. This leads to a set of purchasing operation periods defined as $T = \{t|t = 1,2, \ldots, N_t\}$. Within each time period, purchasing conditions are assumed to be stable. Candidate vendors need to be evaluated regularly (e.g., on a two-week or monthly basis) because of the time-dependency of most of the evaluation criteria. By applying repeatedly the previous methodological steps for each time period, different suppliers' scoring profiles can be calculated per time period (as shown in Table 7 for the numerical example considered). For example, the ranking of the three suppliers calculated before corresponds to the suppliers' scoring profile for March. After obtaining the suppliers' scoring profiles for each considered time frame, an optimization model using the suppliers' ratings as coefficients of the objective function need to be developed, as follows:

Objective function

$$Max(TPV_t) = \sum_{b \in B} \sum_{i_b \in I_b} w_{t,i} F_{t,i_b} \quad \forall t \in T \tag{13}$$

where:

TPV_t = Total Purchasing Value in time period t (including not only economic performance but also total purchasing value in qualitative and quantitative terms), i = supplier index, b = biomass type index, i_b = index of supplier i providing biomass type b, $w_{t,i}$ = significance weight of supplier i in time period t, t = index of the time period considered (e.g., one month), $F_{t,ib}$ = amount of biomass type b to be delivered from supplier i in time period t, I_b = set of suppliers of feedstock type b, B = set of feedstock types and T = set of designated time periods.

Capacity constraints

A supplier i can provide biomass of type b up to a certain amount, $F_{t,i_b}^{\max}$ in each period of time:

$$F_{t,i_b} \le F_{t,i_b}^{\max} \quad \forall t \in T, \forall i_b \in I_b, \forall b \in B \tag{14}$$

Demand constraints

In each time window t, the procured amounts of all biomass types b from all suppliers providing biomass b must sum up to the demand for feedstock, D_t to meet plant's requirements

$$\sum_{b \in B} \sum_{i_b \in I_b} F_{t,i_b} \le D_t \quad \forall t \in T \tag{15}$$

Budget constraints

$$\sum_{b \in B} \sum_{i_b \in I_b} F_{t,i_b} c_{t,i_b} \le C_t^{\max} \quad \forall t \in T \tag{16}$$

where $C_t^{\max}$ refers to the total purchasing budget in time period t and c_{t,i_b} is the total cost for purchasing biomass type b from supplier i in time period t. This cost may change over the total time horizon considered. Thus, the costs need to be estimated periodically (e.g., on a monthly basis).

Quality constraints (optional)

Quality constraints are imposed in order to ensure that required production quality levels are maintained.

$$\sum_{i_b \in I_b} F_{t,i_b} q_{t,i_b} \le D_t Q_{t,b} \quad \forall t \in T, \forall b \in B \tag{17}$$

where $Q_{t,b}$ denotes the buyer's maximum acceptable defect rates for each biomass type b in time period t and q_{t,i_b} is the defect rate of the supplier i with respect to biomass type b at time t.

Non negativity constraints

$$F_{t,i_b} \ge 0 \quad \forall t \in T, \forall i_b \in I_b, \forall b \in B \tag{18}$$

For the numerical example, a set of indicative data can be used (as seen in Tables 8 and 9) based on which the following model is applied to yield the optimal order quantities from the best suppliers considered and maximize total purchasing value for e.g. March:

$$\max(TPV_3) = w_{3,1} F_{3,1_{RP}} + w_{3,2} F_{3,2_{RP}} + w_{3,2} F_{3,2_{SN}} + w_{3,3} F_{3,3_{WCO}} \tag{19}$$

$$\text{or } \max(TPV_3) = 0.278 F_{3,1_{RP}} + 0.340 F_{3,2_{RP}} + 0.340 F_{3,2_{SN}} + 0.382 F_{3,3_{WCO}}$$

Subject to:

$$F_{3,1_{RP}} \le 350 \tag{20}$$

$$F_{3,2_{RP}} \le 200 \tag{21}$$

$$F_{3,2_{SN}} \le 400 \tag{22}$$

$$F_{3,3_{WCO}} \leq 150 \quad (23)$$

$$F_{3,1_{RP}} + F_{3,2_{RP}} + F_{3,2_{SN}} + R_{3,3_{WCO}} \leq 1000 \quad (24)$$

$$c_{3,1}F_{3,1_{RP}} + c_{3,2}F_{3,2_{RP}} + c_{3,2}F_{3,2_{SN}} + c_{3,3}F_{3,3_{WCO}} \leq 9000 \quad (25)$$

$$\text{or } 5.5F_{3,1_{RP}} + 8.0F_{3,2_{RP}} + 8.0F_{3,2_{SN}} + 6.5F_{3,3_{WCO}} \leq 9000$$

$$\text{and } F_{t,i_b} \geq 0 \quad \forall t \in T, \forall i_b \in \{S_{1RP}, S_{2RP}, S_{2SN}, S_{3WCO}\}, \forall b \in \{RP, SN, WCO\}$$

Similarly, the linear programming problem can be repeatedly solved by applying the same model for each month, while making use of the respective parameters shown in Tables 7, 8 and 9. Table 10 indicates the optimal values of biomass amounts purchased by the selected suppliers each month to meet the bioenergy production requirements, along with the maximum total purchasing value obtained by solving the aforementioned model. Due to space limits, Tables 7, 8 and 10 present only data/results for 4 months in one year period. The resulting suppliers' selection profiles and the biomass amounts purchased by the suppliers (i.e., the data included in Table 10) are graphically presented in Figure 1. The results obtained show that suppliers S_2 and S_3 seem to compete for being selected as best suppliers. This finding can be justified by the fact that supplier S_3 represents a low-cost biomass supply alternative (providing inexpensive WCO), whereas S_2 exhibits flexibility in offering the adequate feedstock amounts of two different biomass types (rapeseed and sunflower). It is also obvious that seasonality plays a major role in choosing biomass supply solutions.

Table 10: Results on optimal biomass amounts supplied by each supplier per month and maximum TPV

Months		*b1* from S_1	*b1* from S_2	*b2* from S_2	*b3* from S_3	TPV
January	1	200	300	400	100	354.50
February	2	100	300	450	150	346.05
March	3	250	200	400	150	331.45
…	…	…	…	…	…	…
December	12	200	200	250	350	343.00

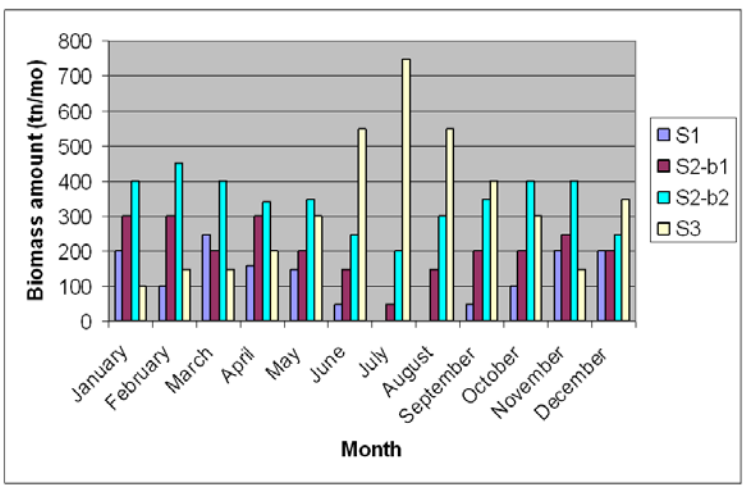

Figure 1: Optimal supply profiles and purchased biomass scheduling

5. Conclusions

The paper presented the effectiveness of a multi-criteria decision making approach for market-sensitive, optimal supplier selection in a biomass supply networks. The approach attempted to demonstrate that the high degree of complexity and uncertainty inherently involved in biomass supply systems renders their management an essentially challenging and dynamically evolved issue with strong impact on the viability of bioenergy production. Outsourcing activities in biomass supply need to take into account the dynamics of the demand in the production system, as well as the cost fluctuations and seasonality of raw material. In achieving sustainable and profitable bioenergy production, it is substantial to consider multiple feedstock sources whose selection for supplying the network depend on time and market conditions. Thus, such a complex and dynamically changing biomass supply environment with high degrees of uncertainties need to be captured by a risk informed decision making approach for estimating, rating and optimizing the biomass supplier profiles with respect to time in a multi sourcing dynamic environment. An interesting future research direction would be to examine the supply performance alternatives, for which demand-driven supply chain models are developed and simulation techniques are employed to experiment with different market scenarios.

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