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A decision support system for supplier selection and order allocation in stochastic, multi-stakeholder and multi-criteria environments

James Scott [a,*], William Ho [b], Prasanta K. Dey [a], Srinivas Talluri [c]

[a] Operations and Information Management Group Aston Business School, Aston University, Birmingham B4 7ET, United Kingdom
[b] Department of Management and Marketing, The University of Melbourne, 198 Berkeley Street, Carlton, Victoria 3010, Australia
[c] Department of Supply Chain Management, Eli Broad Graduate School of Management, N370 Business Complex, Michigan State University, East Lansing, MI 48824, USA

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ABSTRACT

Integrated supplier selection and order allocation is an important decision for both designing and operating supply chains. This decision is often influenced by the concerned stakeholders, suppliers, plant operators and customers in different tiers. As firms continue to seek competitive advantage through supply chain design and operations they aim to create optimized supply chains. This calls for on one hand consideration of multiple conflicting criteria and on the other hand consideration of uncertainties of demand and supply. Although there are studies on supplier selection using advanced mathematical models to cover a stochastic approach, multiple criteria decision making techniques and multiple stakeholder requirements separately, according to authors' knowledge there is no work that integrates these three aspects in a common framework. This paper proposes an integrated method for dealing with such problems using a combined Analytic Hierarchy Process–Quality Function Deployment (AHP–QFD) and chance constrained optimization algorithm approach that selects appropriate suppliers and allocates orders optimally between them. The effectiveness of the proposed decision support system has been demonstrated through application and validation in the bioenergy industry.

1. Introduction

Supplier selection is a typical multi-criteria decision problem (Liao and Rittscher, 2007). Weber and Current (1993) describe the supplier selection problem as which supplier(s) should be selected and how much order quantity should be assigned to each. The problem has attracted widespread interest from both academics and practitioners as firms outsource more and more of their functions to suppliers and continue to compete through supply chains (Wadhwa and Ravindran, 2007; Prajogo et al., 2012). Firms are also involving stakeholder groups in their decision making including bringing stakeholder opinion into the design of new products and services early in the design process (Marsillac and Roh, 2014), especially with regards to environmental and sustainability performance (Aschehoug et al., 2012). This practice has also made it into supply chain decision making as stakeholder influence has become recognized as important to supply chain performance (Polonsky and Ottman, 1998; Klassen and Vereecke, 2012; Miemczyk et al., 2012; Seuring and Gold, 2013). Given the complexity and length of some supply chains the stakeholders impacted by the supplier selection decision are equally complex and varied.

This study addresses the subset of supplier selection problems characterized as requiring multiple suppliers to allocate orders to multiple decision criteria and having multiple stakeholder groups to satisfy. These types of problem are encountered in situations where demand is greater than available supply from a single supplier and where multiple criteria are of interest to the decision maker. Mix and blending problems are a good example of where this type of problem is encountered; often there is also the added complication of uncertainty in the composition of materials being supplied with variation between delivery batch, variation over time and natural variation within deliveries all common. Further complexity is added where the quality criteria of the resulting products are not clearly or crisply defined and there may be some benefit or opportunity in exceeding constraints, alternatively some blending problems will have a tolerance associated with quality criteria of the final product (i.e. the constraint may be specified as 'not exceeding the constraint in more than 2% of tested batches').

Examples of industries facing this type of supplier selection problem include agriculture and the associated food and drink

* Corresponding author.

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supply chain, metal ore purchasing for smelting, plastic and glass recycling and sourcing of feedstocks for chemical processes. Across these sectors millions of dollars' worth of bulk commodities are ordered, shipped, processed and blended before entering the supply chain for higher value products. Small improvements in practice in this area of the economy have a knock on effect efficiency in downstream areas. For example, variations in density of supplied materials can lead to the need for re-working of products or repackaging downstream of other value adding processes, resulting in significant inefficiency. Stakeholder issues also impact these sectors significantly. The agri-supply chain has stakeholder requirements made on it regarding animal rights, sustainable agriculture and disease control for instance, and the recycling industry faces significant issues of contamination and quality control as well as a chain of custody requirement to comply with packaging regulations. These industries have multiple stakeholders each holding a range of opinions, requirements and objectives (Validi et al., 2014). In many industries success against the stakeholder groups' requirements can define the success of the value supply chain. Stakeholder requirements are often not quantitative, rather they are tacit in nature and the supply chain manager must elicit and translate these requirements.

To our best knowledge, there is no comprehensive method for integrating stakeholder requirements into stochastic multi-stakeholder and multi-criteria problems. These are supplier selection problems where multiple suppliers must be selected, multiple stakeholders must be satisfied and the decision must include consideration of multiple quality criteria and those criteria and/or constraints are stochastic in nature. The questions that must be addressed are: (1) how can stakeholder requirements be incorporated into the supplier selection decision, and, (2) what method can be used to optimize multi-supplier selection under uncertain constraint multi-criteria? The contribution of the paper is to demonstrate the integration of methods answering these questions and build them into a decision support system. Specifically the AHP–QFD method is integrated with a multi-criteria chance constrained optimization algorithm. The system was validated by implementing it into the emerging biomass to energy industry.

The rest of the paper is structured as follows. Section 2 reviews the literature of supplier selection and order allocation problems, and identifies the knowledge gaps. Section 3 discusses the conceptual model of the decision support system. Section 4 presents the methodology and approach used in the decision support system. Section 5 applies the decision support system to the integrated problem faced by the bioenergy industry, and Section 6 concludes the paper.

2. Literature review

2.1. Supplier selection problem

Supply chain management in firms have been changing as requirements made of supply chains by customers change. Whilst traditionally firms have sought to increase the efficiency of logistics processes and supply chains to maximize value creation (Quariguasi Frota Neto et al., 2009) more recently value creation has started to come from less obvious avenues (Sundarakani et al., 2010), such as lower risk supply chains (Sundarakani et al., 2010), more robust supply chains (Pan and Nagi, 2010) and a wealth of research on sustainable and green supply chains (Ferretti et al., 2007; Lam et al., 2010; Sundarakani and Souza, 2010) as summarized by Miemczyk et al. (2012). The role of the supplier selection function of supply chain management in these newer supply chain practices has only been partly explored in the literature.

Whilst most literature on sustainable supply chain management considers stakeholders in some regards there are limited studies on multiple stakeholder requirements for supplier selection. Spence and Bourlakis (2009) showed how corporate social responsibility has moved from a focus on the firm to a focus on the supply chain, introducing more stakeholders and complicating the supplier selection process. Wolf (2011) showed how external and internal stakeholder needs, along with supplier characteristics, can be incorporated into supply chain strategy to reduce risk in the supply chain. Reuter et al. (2012) investigated how purchasing managers respond to different stakeholder groups and neatly capture the view that the various stakeholder and shareholder opinions are frequently in conflict, especially in the design of ethical or sustainable supply chains.

Operations research (OR) has an important role to play in supporting solving the supplier selection problem (de Boer et al., 2001). OR methods can enhance the effectiveness of purchasing decisions in several ways including improving the transparency of decision making and better communication about the justification of the outcome (Carter et al., 2000; de Boer et al., 2001), evaluation of suppliers (Bottani and Rizzi, 2008; Amid et al., 2011; Mafakheri et al., 2011; Golmohammadi and Mellat-Parast, 2012; Ekici, 2013). OR methods can also support changing decisions over time (Bottani and Rizzi, 2008; Vanteddu et al., 2011) and decisions made under uncertain conditions (Bai and Sarkis, 2010; Chen et al., 2006; Franca et al., 2010; Liao and Rittscher, 2007; Lin, 2012).

The supplier selection function is dominated by quantitative methods and mathematical modelling. Generally these focus on improvements to the accuracy of supplier assessment and performance or on the method used to rank and select suppliers. According to Ho et al. (2010) methods including AHP, data envelopment analysis, simple multi-attribute rating technique, case based reasoning have all been used to assess the performance of suppliers against multiple criteria. There are many studies in this area showing different methods for supplier selection in various contexts (Mafakheri et al., 2011; Vanteddu et al., 2011; Lin, 2012; Ekici, 2013; Qian, 2014).

2.2. Order allocation problem

Multiple suppliers are commonly required in blending or mixing problems. Often it is infeasible to meet either total demand or the criteria constraints from one single supplier, rather orders must be placed with several suppliers and the material from each blended together to create the final product. The classic example of a linear blending problem, also known as the mixing problem, is shown in Murty and Rao (2004) to blend barrels of different fuel types together to give a required octane rating. The decision maker must decide how many barrels of each constituent fuel type to purchase in order to make a final blend with the required characteristics. There may be limits, costs or constraints associated with the problem and these are represented by constraints for the linear programming model. Further complexity has been added to multiple supplier problems as models become more sophisticated and a better representation of the real business environment. General models for multiple supplier selection have been applied successfully to specific applications in industry, demonstrating the relevance of this approach (Dantzig and Thapa, 2003).

Methods such as linear programming (LP) and mixed integer linear programming (Talluri, 2002; Basnet and Leung, 2005; Hong et al., 2005), goal programming (GP) or genetic algorithms have been applied to help make decisions on supplier selection and order allocation. Extensions of these methods to include stochastic elements and uncertainty have also been made (Burke et al., 2009; Li et al., 2009; Xu and Nozick, 2009; Amin et al., 2011) including fuzzy methods for handling decision maker's fuzzy goals (Nazari-Shirkouhi et al., 2013). Dealing with uncertainty within systems has been a major theme of expansion for novel problem treatments with stochastic or probabilistic methods being introduced (Sakallı et al., 2011) including the use of fuzzy set theory (Rong and Lahdelma, 2008). Li and Chen (2011) proposed a method of integrating stochastic and fuzzy methods with intervals to a linear programme to assist with the problem of transportation in the waste management industry. Hammami et al. (2014) presented a method that can handle multiple suppliers under various currency conditions depending on the suppliers location.

Some blending problems are suited to stochastic methods as the system being modelled may have extensive variation in some or all of the important variables. In some problems variation can be overlooked as insignificant, however in others solutions may be recommended that are clearly sub-optimal or breach constraints. The chance constrained approach was developed by Charnes and Cooper (1959) and according to Verderame et al (2010) has been improved by Lin et al. (2004) and Janak et al. (2007). With the development of fuzzy set theory further extensions and applications to the method were made (Wang, 2004). The chance constrained approach has been applied in several bulk handling fields including coal blending (Shih and Frey, 1995), aggregate blending (Lee and Olson, 1983) and metal casting (Sakallı et al., 2011) amongst others.

2.3. Knowledge gaps

The academic literature on supply chain management and supplier selection has been growing in line with the growing practitioner and customer focus on sustainable supply chains. Whilst the existing literature includes methods to handle various combinations of multiple supplier, multiple stakeholder and multiple criteria supplier selection, there is no available decision support framework that can fully address all of these problems together; translating stakeholder requirements into a stochastic multi-criteria multi-supplier selection decision making process. This situation is faced by industry in several sectors, and such an approach would allow a more holistically successful decision on supplier selection and order allocation to be made by the supply chain designer, and therefore a more sustainable supply chain can be created. There is a need to integrate the available decision support methods into a robust system that can assist practitioners faced with multi-stakeholder, multi-criteria decisions under uncertainty.

3. Methodology

This section describes the development of a decision support system that can integrate a stakeholder requirements method and a stochastic multi-criteria optimization method.

3.1. Development of conceptual model

To develop a conceptual model that could be used to fill the knowledge gaps identified and assist industry in the subset of supplier selection problems of interest a literature review process was used. There are several helpful review papers on multi-criteria decision making for supplier selection, selecting suppliers under uncertain conditions and incorporating stakeholder requirements into the supplier selection decision (Ghodsypour and O'Brien, 1998; de Boer et al., 2001; Kahraman et al., 2003; Aissaoui et al., 2007; Ho et al., 2010; Igarashi et al., 2013).

The challenge of including stakeholder requirements in the supplier selection decision is usually handled in several stages; stakeholder identification, then prioritization or ranking, then the use of some methods for inclusion of stakeholders into the decision process. Various prioritization methods are used with the AHP being amongst the most popular (Ho et al., 2010). Identification of stakeholders has been studied extensively and methods are usually borrowed from the established literature for this purpose (Mitchell et al., 1997; de Vries, 2009; Pacheco and Garcia, 2012).

Having identified the important stakeholders that will be impacted on or can influence the supplier selection decision and the overall success of the supply chain being designed there is then a requirement to incorporate their opinions into the decision process. This is less fully studied in the literature with most authors either mapping stakeholder requirements straight into the objective function according to the importance weighting or eliciting a list of requirements that are then used to measure performance against. This is an important part of the decision system because information lost or misinterpreted at this stage can have a significant influence on the final supply chain success.

Having identified the decision stakeholders and their requirements the next stage is to allocate orders according to the success criteria outlined by the stakeholder group. Because the problem being faced is a multi-criteria problem and we are interested in allocating orders to multiple suppliers the method selected should be able to handle supplier capacities and multi-criteria analysis. The method must also be able to deal with stochastic inputs for uncertain supply criteria. There are many mathematical models that address various parts of this problem. Because the problem of interest here is with regard to mixing and blending applications linear and mixed integer problems are frequently used as identified in the literature review section.

The conceptual model for the decision support system presented in this paper is shown in Fig. 1. Stage 1 of the proposed decision support system uses the AHP–QFD method to translate the importance of different stakeholder groups and the requirements of those stakeholders into a weighted list of evaluating criteria against which any potential supplier can be judged. The full AHP–QFD method for supplier selection was developed by Ho et al. (2011) and applied in Ho et al. (2012), Scott et al. (2013), and Dey et al. (2015). The integrated method has also been used in other industries for different types of selection problem (Hanumaiah et al., 2006; Bhattacharya et al., 2010).

Stage 2 aims to allocate orders to suppliers to maximize stakeholder satisfaction and therefore maximize the success of the overall supply chain. The optimization algorithm must take account of the multiple selection criteria, the constraints on the final product or quality of goods ordered, the stochastic quality measures of the supplied material, the capacity of each supplier to supply material and the supplier score from stage 1.

There are various methods available for stochastic multi-objective optimization including GP (Hu et al., 2007; Li and Hu, 2009; Moghaddam, 2013) and various search algorithms such as pattern search, genetic and evolutionary algorithms and heuristic methods. These methods are not usually used for supplier selection but are applied to other problems in supply chain management (Franca et al., 2010; Mirzapour Al-e-hashem et al., 2011; Moncayo-Martínez and Zhang, 2011; Nearchou, 2011; Validi et al., 2014). Stage 2 could therefore be performed using several different approaches; the method selected will depend on the application.

Stage 3 is a validation of results stage. One of the criticisms of decision support systems in general is the tendency for the human decision maker to distrust the outcome if it appears counter intuitive or sub-optimal (Shim et al., 2002; Arnott and Pervan, 2005). The Monte-Carlo simulation stage of the model overcomes this by using a robust method to show compliance with the technical criteria outlined in the optimization stage.

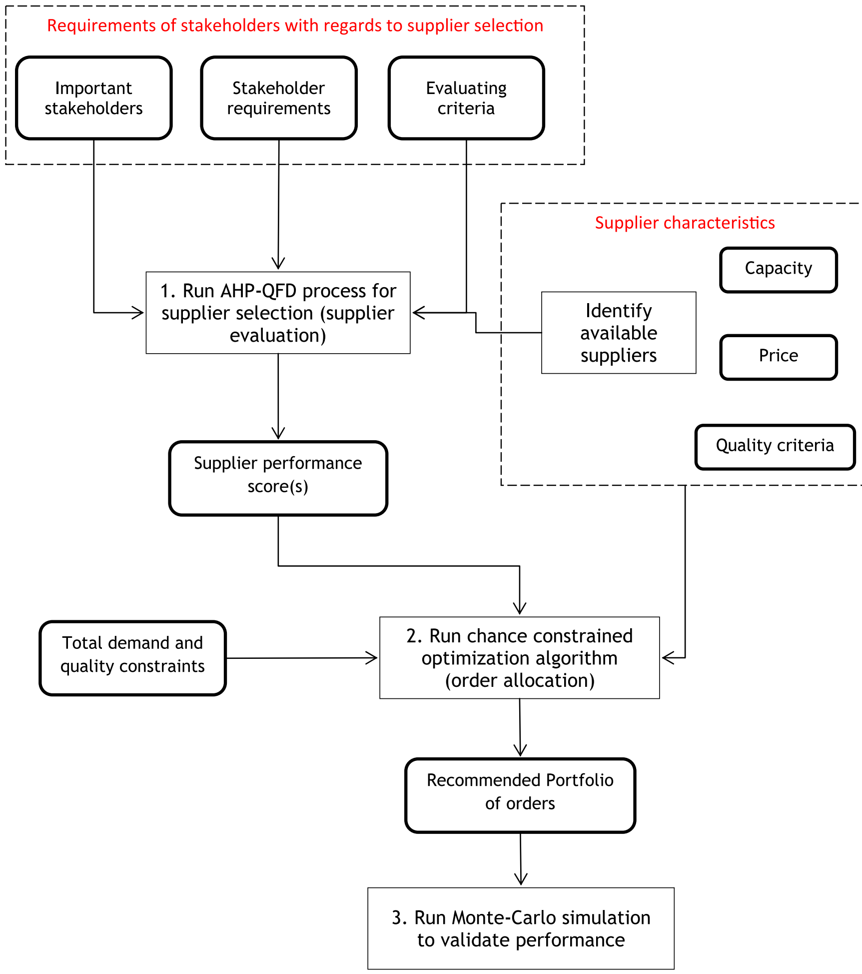

Fig. 1. Conceptual model.

3.2. *Validation through application*

The industry selected for demonstration is the solid biomass to energy industry. In this industry buyers face a complex and influential stakeholder group who tend to focus on supply chain issues and also must purchase from a dynamic and developing supplier market. The variation of natural materials (biomass), the uncertainty in long term supply quality and composition and the complex stakeholder requirements make the buyers problem in this industry an ideal instance of the problem set being studied (multi-stakeholder, multi-criteria, multi-supplier and stochastic supply characteristics).

To ensure that the model is usable and applicable to the target industry and that it provides genuine decision support to the decision maker it has been deployed in a real case study with a bioenergy project developer. Express Energy Ltd. aims to develop new bioenergy projects in the UK using a mixture of residual fuels, recovered woody material and high grade wood products, for the projects to receive permission to operate and structured project finance. Express Energy must demonstrate the presence of a robust, sustainable and holistically successful supply of biomass to the project.

4. The integrated AHP–QFD chance constrained optimization model

AHP–QFD method output (supplier performance scores) are integrated into a chance-constrained model.

Fig. 2 shows an overview of the AHP–QFD method for supplier selection. The requirement importance weighting (output of house of quality 1) is used to give an importance score to the requirements being made by different stakeholders. Then these are translated into an importance score for specific evaluating criteria (output of house of quality 2). These evaluating criteria can finally be used to measure the performance of any given set of suppliers resulting in an array of supplier scores (output of house of quality 3) indicating the extent to which those suppliers satisfy the stakeholder group. The higher the suppliers score the greater the likelihood of stakeholder satisfaction.

The model used to optimize order allocation is shown in this section. The method selected for this application in stage 2 of the conceptual model is chance constrained optimization. The chance constrained model has been selected because it allows for non-crisp constraints to be handled, this is useful in problems where multiple suppliers are involved as they may all provide material with different quality criteria; thus the problem becomes analogous to a mixing problem. There are other optimization methods available that could be used in stage 2 of the model such as LP (useful for blend problems), GP (useful for multiple objective and multiple criteria problems), and various other multi-criteria decision methods that are available in the literature from a variety of industries (Lee and Olson, 1983; Glismann and Gruhn, 2001; Murty and Rao, 2004; Bilgen and Ozkarahan, 2007; Sakallı et al., 2011).

The objective function is to maximize the total stakeholder satisfaction score as shown by Eq. (1). Stakeholder satisfaction is

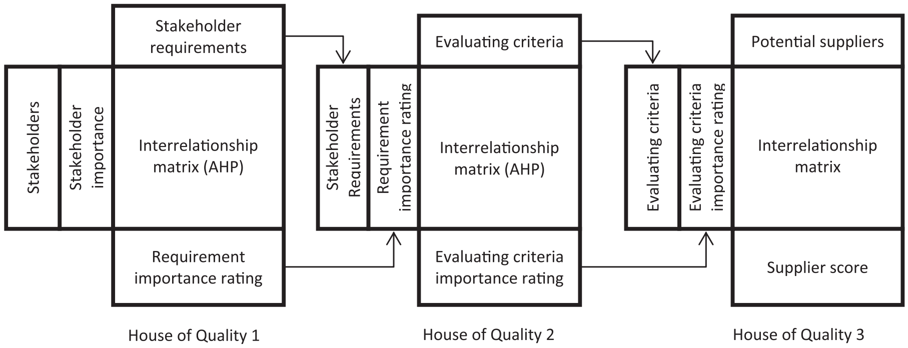

Fig. 2. AHP–QFD method for supplier selection in stage 1. (Adapted from Scott et al. (2013)).

assumed to be linear with relation to the quantity of material taken from each supplier. Notation for the model is shown in Table 1 and the general form of the model is shown in Eqs. (1)–(6).

$$\max : \sum_{i=1}^{n} V_i x_i \tag{1}$$

Subject to:

$$\sum_{i=1}^{n} x_i \geq D \tag{2}$$

$$x_i \leq C_i \ \forall i \tag{3}$$

$$\text{Prob}\left(\frac{\sum_{i=1}^{n} x_i P_{i,j}}{D} \leq \underline{L}_j\right) \leq \underline{p}_j \quad \forall j \tag{4}$$

$$\text{Prob}\left(\frac{\sum_{i=1}^{n} x_i P_{i,j}}{D} \geq \overline{L}_j\right) \leq \overline{p}_j \forall j \tag{5}$$

$$x_i \geq 0 \ \forall i \tag{6}$$

The constraint shown in (2) requires that the quantity of material provided is at least equal to demand such that the generator is not short of fuel. Constraint (3) requires that the orders allocated from each supply source do not exceed the capacity available from that source. The constraint shown in (4) requires that the probability that the blend characteristic for characteristic j is less than the lower constraints for characteristic j is not greater than the corresponding chance constraint. (i.e. the user can allow for the constraint to be breached some of the time). Similarly the constraint in (5) requires the probability of the blend characteristics for characteristic j exceeding the upper limits is less than the corresponding chance constraint as set by the decision maker. This allowance for exceeding constraints is shown graphically in Fig. 3 for a characteristic of the final blended material.

The variable $P_{i,j}$ representing the characteristic j of material from supplier i is the stochastic element of the program. In chance constrained optimization this is the variable changes between the different deterministic equivalent linear programs that are generated for the optimization process. An important element that affects the quality of results obtained from chance constrained programming is the number of deterministic equivalent models that are generated, sometimes referred to as sample number. The greater the number of deterministic equivalent models (the greater the sample number) that can be processed the more accurate the result obtained will be. The chance constrained elements of the model are reported as either satisfied or unsatisfied for each equivalent model created. As with most computational methods, especially when dealing with stochastic problems, there is a compromise between computation speed and accuracy. For the experiments a sample rate of 350 was used and the solver required around 2 min to complete on a 2.6 GHz machine with 4 GB RAM. Even if the sample size is lower to speed up solving time the solver gives solutions that are close to being able to meet the constraints but may exceed constraints slightly more than specified but not greatly. On the other hand if the sample size is too low a clearly non-optimal solution may be produced. This heuristic element of chance constrained programming is a disadvantage to the approach but one that is outweighed by the speed and ease of use once the model is created.

Table 1
Notation.

Indices
i: Supply of material $i=(1, 2, 3, \ldots n)$
j: Material characteristic $j=(1, 2, 3, \ldots m)$
Parameters
V_i: Supplier score
D: Demand
C_i: Capacity of supply i available
$P_{i,j}$: Concentration of characteristic j in material i.
$\underline{L}_j$: The lower constraint for the blend regarding characteristic j.
$\overline{L}_j$: The upper constraint for the blend regarding characteristic j.
$\underline{p}_j$: The user set limit on how frequently the lower limit for characteristic j can be exceeded
$\overline{p}_j$: The user set limit on how frequently the upper limit for characteristic j can be exceeded
Decision variables
x_i: Quantity of orders to be allocated to supplier i.

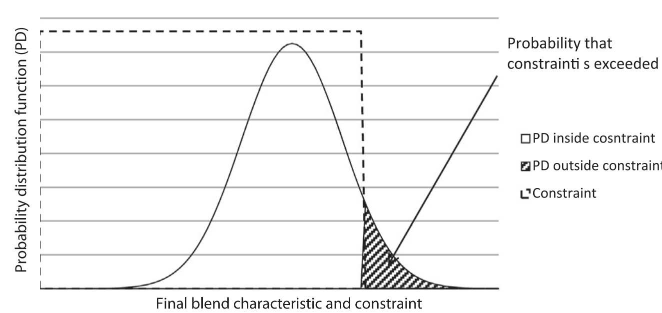

Fig. 3. Chance constrained optimization allows some characteristics to exceed the constraint within the pre-determined chance constraint.

To measure the performance of the recommended portfolio against the constraints associated with the blend properties a Monte-Carlo simulation is used. This involves generating random inputs based on the variation of $P_{i,j}$ to simulate many instances of the constituent feedstocks being blended together. The results of the Monte-Carlo analysis allow the decision maker to test how frequently the recommended portfolio can be expected to exceed the constraints. The Monte-Carlo simulation runs 10,000 iterations for each characteristic of the blend of interest. The general guidance for Monte-Carlo analysis is to use as many iterations as feasible, striking a balance between computation time and accuracy to ensure a proper distribution of results is obtained (Hauskrecht and Singliar, 2002). For the 10 characteristics of interest in this model this required around 20 min to complete and report to an excel spreadsheet. The optimization model was written in the LINGO 13.0 software package and published to run within excel from a macro.

5. Adaption to the bioenergy industry

To demonstrate the efficacy of the proposed model it is applied to the biomass for energy supplier selection problem. This industry problem exhibits the characteristics of interest for the proposed model. This section gives a brief introduction to the industry and the problem being faced by managers aiming to procure biomass fuels.

Biomass refers to organic material that has recently been alive. This definition distinguishes it from fossil fuel based materials and inorganic non-combustible materials. Generally biomass can be considered as wood, agricultural wastes and residues and organic wastes from society. The conversion of biomass to energy involves a linear supply chain starting with harvesting or collection of biomass, pre-treatment of material so that it is suitable for a conversion process and the distribution of energy products with the associated logistics and warehousing challenges between value adding stages. The supply and conversion of biomass to energy is a multi-stakeholder and multi-criteria value chain composed of several key decision points (Iakovou et al., 2010; Adams et al., 2011; Scott et al., 2012; Eswarlal et al., 2014).

To adapt the above conceptual model to be specific and useful enough to address the challenges faced in the biomass industry a series of industry workshops and interviews were conducted. Parties interviewed included developers and operators of both large and small bioenergy schemes, key staff in council planning departments, engineering experts and staff from merchants and dealers of biomass.

Two stages of engagement were used, firstly an open ended conversation with the industry collaborators allowed the problem to be properly defined and the major stakeholder groups and their requirements to be identified. Then a larger number of semi structured interviews were used to identify the specific requirements of stakeholder groups and the related evaluating criteria.

Table A1 in Appendix shows the stakeholder groups that were identified through interviews with technology providers and operators of biomass combustion for electricity generation projects. This technology is well understood in comparison with some of the more novel technologies and the quality criteria are therefore consistent between technology provider. The criteria relate to chemical and physical fuel properties that in turn relate to maintenance requirements in the combustion chamber and heat exchangers, corrosion risk, fuel handling and stack emissions of pollutants. The full table of criteria considered are given in Table A2 in 0.

The model requires some data input to run the analysis. A specification of the expected probability distribution shape for the characteristics j of each fuel supplier or supply to be evaluated i is required. For instance if the characteristic is expected to follow a Gaussian distribution the mean and standard deviation for each $P_{i,j}$ must be specified. The model can handle Gaussian, Weibul, uniform and beta distribution types. The available capacity from each supply C_i, a cost per unit for each supply V_i the total material demanded by the project D, the limits that the blend must comply with $\underline{L}_j$, $\overline{L}_j$ and their associated chance constraints $\underline{p}_j$ and $\overline{p}_j$. The input data that is most difficult for practitioners to identify is the supply characteristics $P_{i,j}$.To counteract this lack of information the presented decision support system uses a data store of biomass materials compiled from various sources and from previous development experience. The data store allows the decision maker to select a material description that closely matches the material available and to estimate its characteristics for situations where complete analytical data is unavailable. As more information is gathered on specific available supplies the user can update the data store with more accurate information. For the implementation shown below data on fuel sources is compiled from the EU BioDat database (ECN, 2013) and other literature sources on biomass (Huang et al., 2007; van Loo and Koppejan, 2008; Vamvuka and Kakaras, 2011; Vassilev et al., 2010; 2013). Standards for biofuels and waste derived fuels are also included in the data

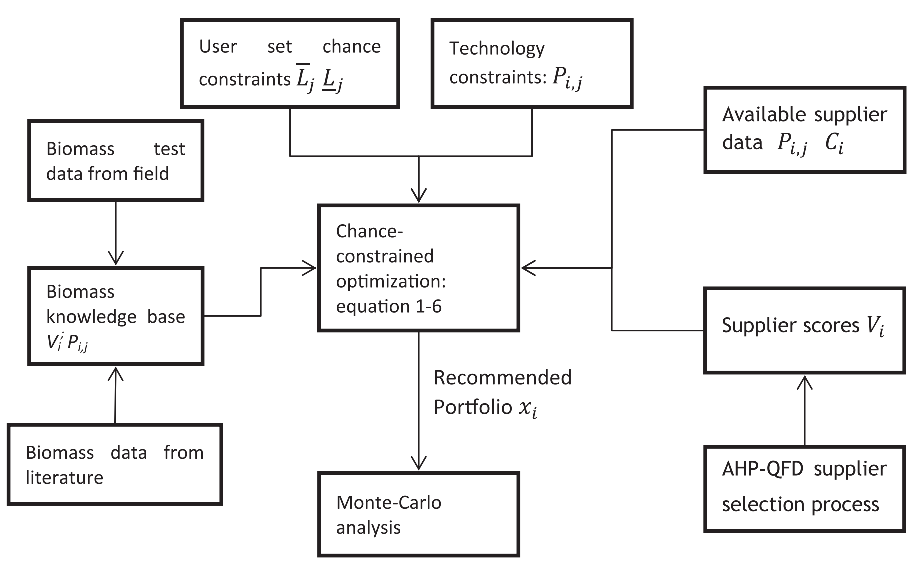

Fig. 4. Data flow through the decision support system.

store (van Tubergen et al., 2005; Christensen and Rotter, 2010; Loibnegger, 2010). Fig. 4 shows the dataflow through the decision support system. Information on material characteristics is contained in a knowledge base that could be enhanced through the use of ontology of the domain. Supplier scores from the AHP–QFD supplier selection process become V_i in the model.

5.1. Application to bioenergy buyer's case

The problem faced by biomass to energy power stations and their fuel supply chain is to ensure that fuel supply contracts are arranged in such a way that the technical requirements of the conversion plant are met and the project is attractive to the important stakeholders.

There are many different chemical and physical constraints that are set by the exact type of technology selected for the project. A technology provider may provide a conditional warranty for instance, indicating that the warranty is only valid if a fuel within a particular standard or requirement is used. Typically this warranty requirement is well within the actual operating parameters of the plant and is of finite length. Exceeding the warranty conditions or the operating parameters can have different impacts depending on the type of chemical constraint that is exceeded. Sometimes exceeding a constraint may mean that pollutant emissions are increased, sometimes that efficiency is decreased, sometimes that maintenance costs may increase or plant availability may be reduced.

To further complicate this problem the characteristics of the fuel may vary over time, between deliveries and even within a single delivery. This means that the buyer is uncertain of exactly what the chemical properties of a given batch of material will be. An extensive sampling regime can combat this problem but even if every kilogram of material was tested there would still be a natural variation of characteristics given the natural origins of the material. For some materials this variation is very wide.

From conversations with the industry this is currently resolved through clauses within contracts drawn up between suppliers and buyers, the supplier will agree to deliver material within particular constraints specified within the contract, however, this approach is ultimately unsatisfactory as if material is found to be in breach of the contract the generator cannot operate and the losses cannot be covered by the small supplier company regardless of contract conditions.

The problem of uncertain characteristics is reduced when material has undergone pre-processing and is more of a homogenized tradable commodity, however this also pushes up the material price. The cheaper materials tend to have larger variation and less testing or quality control, these are often described as "waste" or "residual" materials. The challenge is compounded by the buyer not always knowing exactly what the resource is when negotiating for a supply contract. For instance the description of 'wood waste' may cover a range of sources and materials which themselves may have a wide range of properties.

The bioenergy buyer's problem is therefore to allocate orders between the available suppliers in such a way that chemical, energetic and total demand constraints as definedby the technology being constructed are satisfied whilst also maximizing stakeholder satisfaction. The model presented in this paper provides a tool that can assist in making this decision. The tool gives a rapid assessment of the impact of potential new fuel supplies being introduced in to the supply portfolio and gives an accurate price for the overall feedstock blend.

5.2. Model specification

The technology being used for the conversion process requires a fuel (final fuel blend) that has properties within the constraints shown as the upper and lower limits in Table 2. Each characteristic also has an associated chance constraint that represents the likelihood that the constraint can be breached. A tolerance of 1 means the constraint cannot be breached. A tolerance of 0.8 means the constraint can be exceeded 20% of the time and the solution can still be accepted as feasible. This information has been aggregated from 3 different industry projects using different technology providers. This means that although the limits are representative of situations faced in industry the data presented does not compromise confidentiality of the participating parties.

The suppliers available to the buyer are: a supplier of wood from a building demolition company; a supplier of refuse derived fuel that is sourced from municipal waste streams; a limited supply of wood chips; a supply of residues from the olive production process and a supply of expensive but high quality wood pellets. Each source has different chemical properties, availability and price. This information has been provided by the industry partners anonymously and has been checked against literature databases (ECN, 2013). The different supplies also have an associated supplier performance score according to the AHP–QFD method. The final scores have been assigned by the buyer according to the evaluating criteria importance weightings from Scott et al. (2013) as shown in Table A3 in Appendix. The score, rank, availability and associated price of each supply of biomass are shown in Table 3.

The refuse derived fuel is the cheapest available and is the most preferable for the stakeholder requirements. However, it has some

Table 3
Score, capacity and unit price for each supplier.

Supplier	Supplier score	Rank	Capacity (tonnes/year)	Unit cost (£/tonne)
Demolition wood	0.176	4th	10,000	£25.00
Refuse derived fuel	0.269	1st	10,000	−£5.00
Wood chips	0.141	5th	5000	£50.00
Olive residues	0.225	2nd	7500	£25.00
Wood pellets	0.188	3rd	8000	£85.00
Total	**1.000**		**40,500**	

Table 2
Chemical constraints and associated chance constraints for the conversion technology.

Characteristics **Units**	**Biomass** **wt%**	**Moisture** **%**	**Lower heating** **MJ/kg**	**Ash content** **wt%**	**F** **mg/kg**	**Na** **mg/kg**	**K** **mg/kg**	**Al** **mg/kg**
Lower limits	90	5	10.0	–	–	–	0	–
Upper limits	100	20	21.0	6	280	10,000	8000	700
Lower tolerance	1	1	0.8	–	–	–	1	–
Upper tolerance	–	0.8	0.98	0.75	0.95	0.9	0.8	0.95

disadvantages as it has higher pollutant levels and lower biomass energy content than the other supplies. The wood pellets have less impurities and ash but do not score as highly for the stakeholder requirements. The wood chips supply is not favoured by the stakeholder group according to the AHP–QFD process.

The final point of data required is the projects total demand. For this project the buyer required 18,000 tonnes of biomass per year for use in a combustion system. With this information the decision support system is now fully specified and the chance constrained program can be run to find the blend of suppliers that will best satisfy the requirements of the stakeholder group.

5.3. Results

The resulting recommended portfolio is shown in Table 4 and Fig. 5.

The objective function for this portfolio is 3758.6. The LINGO solver produced a global optimum output using a sample number of 1200. The solver required 1 min 10 s to find a solution.

To check the accuracy of the result the Monte-Carlo part of decision support system is now used. Using the known fuel characteristics and the recommended order quantity a new instance of the blend characteristics is calculated for each iteration of the Monte-Carlo simulation. 10,000 iterations are completed for each characteristic. The simulated points can then be compared with the constraints from Table 2 to ensure the chance constrained program has found an accurate solution. In the case being tested the binding constraint is found to be the upper limit of Fluorine content (F). Table 2 shows that the buyer will allow a 5% exceedance of this limit, the Monte-Carlo result is that there is a 4.8% chance that the recommended blend will exceed the limit of 280 mg/kg, within the 5% tolerance and therefore a feasible solution. The other chemical constraints are not found to be binding although the supply of both olive residues and wood pellets is entirely used (contracted up to the available amount) and these constraints are also binding.

Table 4
Recommended portfolio of orders to allocate between suppliers.

Supplier	Recommended amount to contract for	Percentage of final fuel blend (%)
Demolition wood	1198.9	6.7
Refuse derived fuel	1301.1	7.2
Wood chips	0.0	0.0
Olive residues	7500.0	41.7
Wood pellets	8000.0	44.4
Total	18,000.0	100

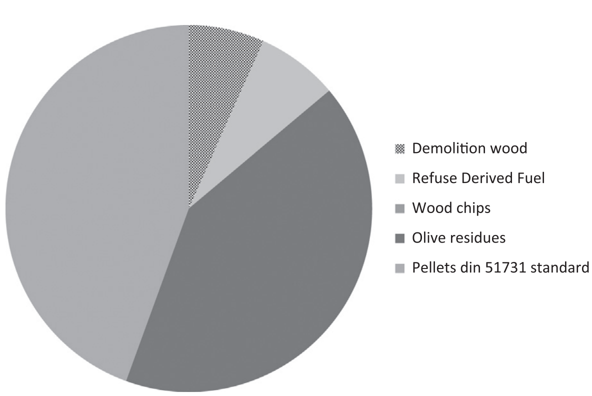

Fig. 5. Recommended portfolio.

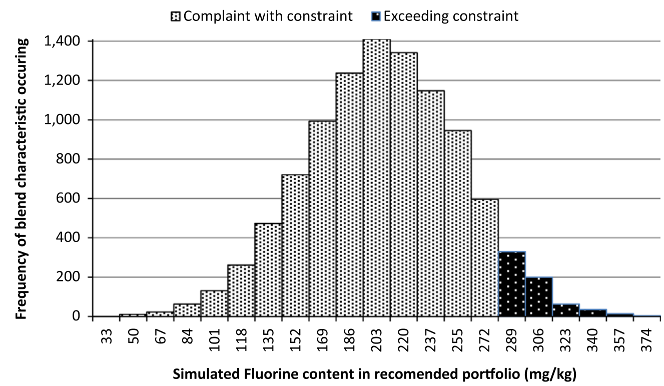

Fig. 6. Fluorine content in portfolio according to Monte-Carlo simulation.

The Monte-Carlo result for fluorine content in the recommended blend is shown in Fig. 6 with the likelihood of the blend properties falling outside of the 280 mg/kg constraint coloured dark.

The computation time for the decision support system could be improved by using a more powerful computer, however considering that this type of solution will likely be required less than once per day by the decision maker the computational efficiency is acceptable. The decisions support system also has a mechanism for displaying error messages when the solution is found to be infeasible or when the model is not fully specified.

The Monte-Carlo stage is useful for building trust in the obtained solution. Without this step there is no evidence for the performance of the chance-constrained algorithm and the decision maker may consider that the system could be flawed or be making a sub-optimal selection, especially when the solution appears counter intuitive at first. By converting the stakeholder group into requirements and then into evaluating criteria and supplier performance measurements mean the decision maker now has an empirical measure of performance. This allows stakeholder satisfaction to be written into the objective function, removing the subjectivity of the decision maker themselves. Areas where decision maker opinion is used are in the assessment of stakeholder importance and in the assessment of suppliers against evaluating criteria.

6. Conclusion

The presented model has been shown to successfully integrate the requirements of stakeholders into the decision making process for supplier selection. By using the AHP–QFD method a set of evaluating criteria scores are created against which suppliers can be judged. This has several positive effects for the decision maker and the supply chain as a whole. Firstly the decision maker has a clear mandate for how to place orders according to stakeholder wishes. The decision makers own subjective judgement is removed from the equation and replaced by an empirical representation of the tacit requirements of the stakeholder group. Secondly, if the evaluating criteria weightings are communicated to potential suppliers those suppliers can respond accordingly. Suppliers can develop their offering in full knowledge of the performance criteria they will be competing on. Thirdly the stakeholder group are properly consulted before the order allocations are made; this prevents the supply chain manager second guessing their stakeholder requirements and brings the requirements of stakeholders to the fore.

If stakeholders remain unsatisfied by the managers decision they too now have a clear route for response, they can position themselves to have greater salience in the success of the supply chain and thus become further empowered as agents in the creation of successful supply chains. The remaining subjective element on which the buyer must pass judgement are with regards to the importance of each stakeholder group. The accuracy of stakeholder importance weightings can impact on the overall success of the final decision. Therefore this remains an area for potential improvement in the presented model. There are various weighting and scoring methods available to assist with this stage of the AHP–QFD that could also be integrated into the decision framework.

The proposed model has been applied to a problem in the bioenergy industry where it is manifested as a blend or mixing problem. Similar problems exist in the food ingredients supply chain, the agricultural supply chain for grain and feed mixing and the metal smelting and fuel blending industries. By following similar steps of capturing available information, understanding the stakeholder groups and their requirements and the decision constrains and criteria each of these industries could make use of the presented general model.

By ensuring that the conventional quality criteria can be incorporated into the decision the presented model does not introduce a compromise between the quality of materials purchased and stakeholder satisfaction. However, a compromise is naturally introduced between optimum price and optimum stakeholder satisfaction. In its presented form the model is only applicable where decisions are made regardless of price. The model could be extended by including some consideration of price into the model, the authors suggested approach for the presented case would be to create a layer of goal programming code that sets an acceptable total supply price. Where the price represents the limit at which the project can be economically sustainable. It is not recommended to take a similar approach for stakeholder satisfaction, the aim of using this method is to better meet the needs of the supply chain stakeholders, imposing artificial targets on performance could lead to counter intuitive solutions from the perspective of a particular stakeholder.

The model also does not consider minimum order quantities, batch sizes and inventory management that may be important for the successful allocation of orders at the operational decision level. Methods demonstrating how these constraints can be included can be found in the literature (Chung and Wee, 2007; Rau and OuYang, 2008; Song et al., 2013). Further improvement could be made through introducing more sophisticated data management techniques for handling the performance of suppliers over time and especially for making accurate estimates of the probability distribution function that should be expected from a supplied material for each quality criteria. This could compliment the knowledge base part of the biomass specific model.

The presented integrated AHP–QFD chance constrained optimization method has been shown to allow for order allocation to be optimized against stakeholder requirements with uncertain supply characteristics and with non-crisp constraints. It can be used to address multi-stakeholder, multi-supplier, multi-criteria stochastic problems. This is the contribution of this work. The presented model has been shown to assist with supplier selection in problems such as that faced when procuring biomass for energy projects. This contributes to the range of support tools available in the literature to the industry.

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Appendix

See Tables A1–A3.

Table A1
Participants involved from each stakeholder group.

Bioenergy stakeholder group	Number of participants
Financial groups and project partners/investors	5
Environmental groups	3 plus documentation
Developers/operators and utilities	5
National government and policy makers	Documentation only
Local government	4 plus documentation
Community/public	4

Table A2
Quality criteria of fuels according to technology provider.

Criteria	**Unit of measurement**	**Comments**
Biomass energy content	%	To qualify for renewable energy financial incentives the bioenergy content of the fuel must be over 90% (UK only)
Moisture content	Percentage weight (wt%)	The amount of water in the material can affect efficiency and corrosion of the conversion process
Lower heating value (energy content)	Megajoules per kilogram (MJ/kg)	The energy density of the material affects the efficiency and operating hours of the conversion plant
Ash content	wt%	The non-combustible fraction of the fuel can cause problems associated with corrosion and clogging of feed mechanisms
Non-metal impurities: sodium (Na), potassium (K), fluorine (F)	mg/kg	Under certain conditions these elements can lead to the creation of corrosive acids and are controlled under emissions regulation
Aluminium (Al)	mg/kg	Can lead to corrosion of equipment and are tightly controlled under emissions regulations

Table A3
Supplier scores and weightings (Scott et al., 2013).

Evaluating criteria	Evaluating criteria importance score	Demolition wood	Refuse derived fuel	Wood chips	Olive residues	Wood Pellets
Long term contracts	0.0226	8	0	2	7	1
Take or pay clauses	0.0539	5	6	0	10	7
Track record	0.1098	5	4	3	4	5
personal relationship	0.0125	4	6	9	7	2
Contract has PFI back up	0.0131	2	7	0	6	8
Fixed price	0.0571	8	5	8	7	3
Traceable (chain of custody)	0.0169	5	6	4	6	1
Base cost of material (£/MWh)	0.0684	5	7	1	8	5
Clear definition of fuel	0.0098	6	5	0	4	7
Visibility	0.0132	2	0	10	10	6
Quality control mechanisms in place	0.0034	3	5	1	6	2
Guarantee of fuel quality available	0.0529	2	10	4	10	9
Supplier stability (in biomass market)	0.0061	0	0	5	9	1
Distance from buyer	0.0008	4	1	5	3	9
CO_2/MWh	0.0779	2	4	3	7	5
Land use change	0.0327	1	10	0	7	8
FSC accreditation	0.0116	4	4	6	6	9
Alternative end use (best use of biomass)	0.0196	7	0	4	7	7
Diversion of material from landfill	0.0411	4	6	10	8	3
Environmental regulatory environment in which the supplier operates	0.0068	9	5	9	7	4
Performance against sustainability assurance certificate indicators	0.0145	0	1	9	10	6
Credit strength	0.0398	2	9	4	7	8
Size of balance sheet	0.0172	2	2	1	10	6
Financially robust or credible counterparty	0.1490	2	7	3	1	2
Rural jobs created or safeguarded	0.0919	5	8	1	1	3
Dependency on imports	0.0066	8	4	6	0	8
SME employment created	0.0459	8	9	3	6	2
Biodiversity change	0.0053	4	6	4	10	1
Total	1.000	117	137	115	184	138
Normalized score		0.176	0.269	0.141	0.225	0.188
Rank		4	1	5	2	3

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