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Dealing with uncertainties of green supplier selection: a fuzzy approach

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Abstract: Increasing public awareness of environmental protection has caused the emergence of green supply chain management in recent years. As firms tend to outsource a significant part of their activities, the importance of supplier selection increases from a competitive standpoint. While most studies of supplier selection have introduced methods based on economic criteria, the number of studies that incorporate environmental issues is rather limited. In this paper, a methodology is proposed to address the green supplier evaluation and selection issue by first identifying the appropriate criteria and then developing a model for their measurement in the evaluation process. The authors apply fuzzy set theory to deal with the subjectivity of supplier selection decision-making and capture the linguistic terms used for human assessments. A rule-based fuzzy inference system is developed to evaluate suppliers based on ten environmental criteria and eventually select the best-performing supplier. The dynamic nature of the model allows the decision-makers to manipulate the importance of different supplier attributes and constructed rules, based on individual preferences. An illustrative example is also presented to show the applicability and effectiveness of the proposed methodology.

Keywords: supplier evaluation, supplier selection, supply chain economics, uncertainty, fuzzy logic, fuzzy inference system

JEL codes: C44, D81, D91

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1 Introduction

Growing competition between companies has increased the importance of the effectiveness of supply chain management (SCM), which is a combination of systematic activities that manage the flow of goods and services within a system of organizations. It starts from the initial customer order of raw materials and involves every stage up until final delivery of ready products to end consumers. Along the whole supply chain, companies often focus on some of these tasks while outsourcing a significant part of their activities. Moreover, today's business environment is characterized by increasing ambiguity, unsteadiness, and unpredictability. Organizations take every opportunity to advance their competitive position in the market. Therefore, selection of trading partners has significant influence on the performance of the entire supply chain network. Supplier assessment and selection is an important strategic decision for minimizing operating costs and enhancing organizational efficiency.

Supplier selection is described in the academic and practitioner literature as a very complex task where multiple factors influence the decision-making process (Kumar et al., 2014). Furthermore, the number of potential trading partners tends to increase in every industry, which makes the selection process even more challenging (Bai and Sarkis, 2010). Consequently, supplier selection problems are highly associated with uncertainty as they depend on subjective judgements of decision-makers (Li et al., 2007). The exact values of all criteria are not always available, which forces the experts to often evaluate suppliers using linguistic variables. As a result, decision making models that are able to capture this vagueness are more likely to provide realistic results.

Previous studies of supplier selection have focused primarily on economic rather than ecological efficiency of suppliers and rarely taken environmental issues into account. At the same time, public awareness of environmental protection has increased considerably over the past few decades. The concept of green supply chain management (GSCM) is becoming increasingly critical due to constant pressures exerted by governments, policy institutions and the general public. Given the importance of supplier selection amongst various functions of a supply chain, companies are held responsible not only for their own actions, but also for the impact of their trading partners on the environment (Jayaraman et al., 2007; Wu & Barnes, 2016). As a result of the growing consciousness, GSCM has started appearing more often in recent literature (Khaskar et al., 2016; Yazdani et al., 2017).

This paper seeks to identify a complete and exhaustive list of green supplier evaluation criteria and develop a fuzzy logic scheme to compere different supplier profiles in the decision-making process. Ten green supplier selection criteria are identified and used as inputs for a fuzzy logic-based decision support model which generates the competitive positions of different suppliers as outputs. The application of the suggested methodology is presented through a numerical example. The robustness of the model is tested by applying different fuzzy membership functions and defuzzification methods, as well as running multiple supplier comparison scenarios.

The remainder of the paper is constructed as follows: section 2 introduces a review of the relevant literature. Section 3 presents the research methodology applied in this study explaining fuzzy set theory and how it is utilized for supplier selection. The problem of interest is formulated in section 4, and the results of the constructed model are presented in section 5,which includes a numerical case and a discussion. Section 6 summarizes the analysis and offers recommendations for future research.

2 Literature review

This section offers an overview of supplier selection methods and criteria in the existing literature, with a particular focus on GSCM. Green supplier selection considers numerous qualitative and quantitative factors and is formulated as a multi-criteria decision-making (MCDM) problem. Over the past few decades, numerous supplier selection methods have been proposed to deal with the complexity of this task, including researches conducted by de Boer et al. (2001), Ho et al. (2010), Chai et al. (2013), and Govindan et al. (2015). MCDM techniques such as the analytical hierarchy process (Levary, 2008; Grisi et al., 2010) and the analytical network process (Sarkis, 2003; Tseng et al., 2009; Hsu and Hu, 2009) have been widely applied to the supplier selection problem both individually and in integration with other methods (Govindan et al., 2015). Other popular integrated approaches include different combinations with fuzzy set theory (Kumar et al., 2004; Li et al., 2009), compromise programming (Shemshadi et al., 2011; Bhutia and Phipon, 2012), goal programming (Erdem and Göcen, 2012), integrated Delphi methods (Liao, 2010; Karbassi Yazdi et al., 2018; Kaviani et al., 2019).

Although the existing research addressing green supplier evaluation and considering environmental factors is rather limited, there is a growing interest amongst researchers to develop MCDM models that can strengthen GSCM. Govindan and Sivakumar (2016) applied fuzzy TOPSIS and multi-objective linear programming (MOLP) to assign purchase orders to different suppliers. They aim at minimizing cost, late delivery, material rejection, and CO_2 emissions in the production process. Kannan et al. (2013) determined a combination of economic and environmental indicators to assess green suppliers, including cost, quality, delivery, technological capability, and environmental competency. These authors used fuzzy AHP and fuzzy TOPSIS to obtain supplier performance values. Gören (2018) developed a GSCM decision framework based on DEMANTEL. The latter was used to determine the weights of the supplier criteria, and Taguchi Loss Functions were used to assess the performance of each supplier. Park et al. (2018) applied multi-attribute utility theory and multi-objective integer linear programming to address a multi-objective supplier selection problem. Their study aimed at minimizing cost, order defect, carbon footprint, and delivery delay.

Independent of the chosen methodology, identification of supplier evaluation and selection criteria is the foundation of the supplier selection problem (Celebi and Bayraktar, 2008). Initial works of supplier selection were solely based on criteria with economic impact on firms and organizations. These economic criteria have been consistently explored and investigated in the literature over the past four decades, starting with the early work by Dickson (1966). Along with organizations moving in the direction of green supply chains, it has become essential to incorporate green supplier attributes into the decision-making process. The earliest efforts to take into account environmental criteria included works by Lamming and Hampson (1996), Sarkis et al, (1996), Noci (1997). More recent works have tried to build upon those early researches and address more comprehensive lists of green attributes (Lee et al., 2009; Amindoust et al., 2012; Hashemi et al., 2015). The most commonly used criteria include pollution/waste control in production, green packaging, green design, reverse logistics, green materials, green product, green distribution, green image. It is worth mentioning that these criteria are described with different wording in different papers. At the same time, most of the above-mentioned studies discuss environmental aspects as part of the overall supplier assessment and do not specifically focus on developing and considering an exhaustive list of green attributes. There is a lack of comprehensive analyses evaluating suppliers solely from environmental friendliness perspective. In addition, very few existing models address the uncertainty of supplier selection in a GSCM setup. Both the identification of relevant green supplier attributes and the evaluation of different supplier with respect to those criteria are affected by subjectivity and vagueness of the decision-making process. Often it is impossible for decision-makers to express their preferences in pure numeric scales and linguistic terms are required to capture the subjectivity of human assessments (Ordoobadi, 2009).

Fuzzy set theory is a powerful methodology that allows to cope with real-life situations involving imprecision and ambiguity. Fuzzy logic has been widely used in different disciplines with decision-making under multiple criteria. Paul and Azeem (2010a) proposed a model for the optimization of shift periods considering inventory information, customer requirements, and machine reliability using fuzzy logic. Sun (2010) developed a performance evaluation model based on fuzzy analytic hierarchy process where the vagueness and subjectivity are handled with linguistic values. Paul (2013) proposes a fuzzy approach to prioritize and sequence different jobs on one machine based on multiple input variables. This author considers arrival order, processing time, due date, slack time remaining and several other factors to make the sequencing more realistic. Fuzzy logic has also been used to create a decision-making system for livestock service management (Sivamani, et al., 2017). These authors take diet and health management into consideration to increase the productivity of livestock.

Fuzzy set theory has also seen some applications in the supplier selection literature. Ordoobadi (2009) was perhaps one of the first authors to point out the necessity of dealing with ambiguity in supplier selection decision-making. This study develops a simple decision model that captures decision-makers' preferences which are expressed in linguistic terms. Based on those preferences, supplier selection attributes are evaluated, and the performance of suppliers is measured using a fuzzy inference system. The author recommends implementing the proposed methodology into a computer-based software as a direction of future research. He also recommends developing the model further by suggesting a more targeted list of selection criteria and achieving more robust model specifications (e.g. testing the results with different input membership functions or defuzzification methods).

The next group of studies is primarily based on the fuzzy logic toolbox in MATLAB and creates rule-based fuzzy inference systems to assess suppliers. Kumar et al. (2011) conducted an analysis based on fuzzy logic for Indian textile organizations. The data was collected from a survey of 66 textile organizations. Fuzzy set theory was applied to decide on selecting or rejecting a particular supplier. Osiro, et al. (2014) proposed a fuzzy logic method for supplier evaluation, analyzing the gap between real and expected performance. They apply this method to a company in the automotive sector to show how it can work in practice. Hasan et al. (2015) develop a fuzzy model with ten supplier evaluation criteria. Fuzzy control is used to determine the best supplier based on calculated scores. The results were tested on the example of a flexible intermediate bulk container manufacturing company. Paul (2015) proposed a fuzzy inference system for managing supply risks. He identified eighteen quantitative and qualitative selection criteria and developed 168 rules relating all those criteria to final outputs.

Although some of the above-mentioned supplier selection studies have considered certain environmental criteria, to the best of our knowledge, none of the previous researches have specifically focused on the impact of environmental factors while utilizing fuzzy set theory. In this paper, we propose a flexible rule-based supplier selection model to handle the subjectivity of the decision-making process for green supplier selection. Ten environmental criteria have been identified and considered as inputs for the proposed model. In the simplest-case scenario, decision-makers can only specify the list of suppliers they want to evaluate and where those suppliers stand in terms of the ten environmental criteria. As a result, the ranking index of the suppliers is created. At the same time, the model allows for changes in the order of importance of the attributes, shapes of the membership functions, defuzzification methods, and to create additional outputs.

Unlike all the previous efforts in this domain, we decided to work with an analogous set of algorithms in Python called scikit-fuzzy, which is able to produce similar outputs as the MATLAB toolbox. It also allows for more flexibility based on individual preferences. To the author's knowledge, this is the first effort in the literature that utilizes the scikit-fuzzy algorithms to deal with uncertainties of the supplier selection process. The main contributions of this study include identification of ten exhaustive criteria for green supplier selection, development of a flexible rule-based fuzzy inference system, and capturing the ambiguity of the decision-making process. In the following section, the research methodology of this study is presented, followed by the setup of the fuzzy inference system, as well as the results of our model.

3 Research methods

This section introduces a fuzzy logic approach to address the uncertainties of supplier selection decision-making. First, a brief of overview of the theory and fuzzy logic is provided, followed by the explanation of the scikit-fuzzy algorithm and the fuzzy inference set constructed for our green supplier selection problem.

3.1 Fuzzy set theory and fuzzy logic

Fuzzy set theory was introduced by Zadeh (1965) in his seminal paper 'Fuzzy sets' in Information and Control. Fuzzy logic is used to address the ambiguity of human assessment. Rather than applying the typical 'true or false' (1 or 0) Boolean logic, fuzzy logic is based on 'degrees of truth'. It is a way of processing data by allowing partial set membership instead of crisp set membership or non-membership. This approach deals with the concept of partial truth, where the truth value ranges from completely true to completely false. A fuzzy set $\tilde{A}$ in X is defined by

$$\tilde{A} = \{x, \mu_F(x)\}, \qquad x \epsilon X \tag{1}$$

where $\mu_A(x)\colon X \to [0,1]$ is the membership function of $\tilde{A}$ and $\mu_A(x)$ is the degree of pertinence of x in $\tilde{A}$. If $\mu_A(x)$ equals 0, x does not belong to the fuzzy set $\tilde{A}$. If $\mu_A(x)$ equals 1, x completely belongs to the fuzzy set $\tilde{A}$. If $\mu_A(x)$ has a value between 0 and 1, x partially belongs to the fuzzy set $\tilde{A}$. That is, the pertinence of x is true with a degree of membership given by $\mu_A(x)$ (Zadeh, 1965; Zimmermann, 1991).

In fuzzy set theory, fuzzy numbers are used to deal with ambiguity in decision-making. A fuzzy number is a fuzzy set in which the membership function satisfies the conditions of normality

$$\sup \tilde{A}\,[X]_{x \epsilon X} = 1 \tag{2}$$

and convexity

$$\tilde{A}[\lambda x_1 + (1-\lambda)x_2 \geq min[A(x_1), A(x_2)]] \tag{3}$$

for all $x_1, x_2 \epsilon X$ and all $\lambda \epsilon [0,1]$. Fuzzy relations represent and quantify associations between objects (Osiro et al., 2014). A relation R defined over the Cartesian product of X and Y sets is a collection of selected pairs *(x, y)* expressed by

$$R\colon\ X \times Y \to [0,1] \tag{4}$$

where $x \epsilon X$ and $y \epsilon Y$. If $R\ (x, y) = 1$, then x and y are related. If $R\ (x, y) = 0$, then these two elements are unrelated. If $0 < R\ (x, y) < 1$, then there is a partial association between x and y (Pedrycz and Gomide, 2007; Kahraman, 2008).

Membership functions can take on different types of shapes, such as triangular, trapezoidal, and Gaussian representations. The triangular fuzzy number (TFN) is often used in multi-criteria decision-making and can be donated as $M = (l,\ m,\ u)$. Its membership function $\mu_M(x)\colon R \to [0,1]$ is equal to:

$$\mu_m(x) = \begin{cases} \frac{x}{m-l} - \frac{l}{m-l} & , \ x \in [l, m] \\ \frac{x}{m-u} - \frac{u}{m-u} & , \ x \in [m, u] \\ 0 & , \ Otherwise \end{cases} \quad (5)$$

where $l \leq m \leq u$. *l, m*, and *u* are the lower, mode, and upper values of the support of M, respectively. When $l = m = u$, it is a non-fuzzy number by convention (Chang, 1996). The main operational laws for two triangular fuzzy numbers M_1 and M_2 are as follows (Kaufmann and Gupta, 1991):

$$M_1 + M_2 = (l_1 + l_2, m_1 + m_2, u_1 + u_2), \quad (6)$$

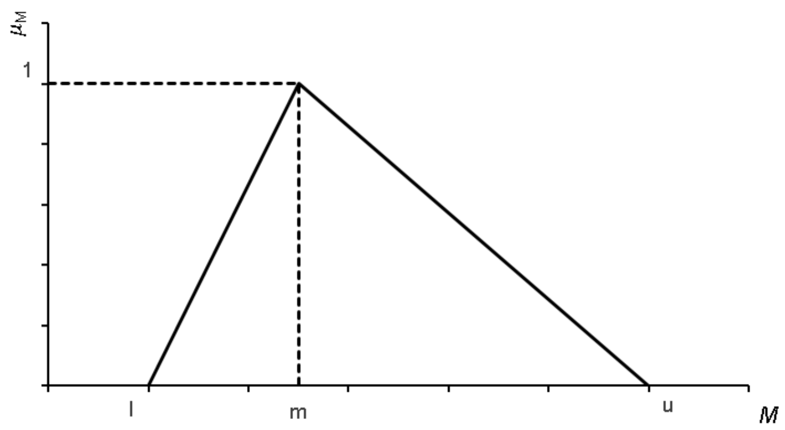
$$M_1 \oplus M_2 = (l_1 l_2, m_1 m_2, u_1 u_2), \quad (7)$$

$$\lambda \oplus M_1 = (\lambda l_1, \lambda m_1, \lambda u_1), \lambda > 0, \lambda \in R, \quad (8)$$

$$M_1^{-1} = (1/l_1, 1/m_1, 1/u_1) \quad (9)$$

Figure 1 shows the membership function of a triangular fuzzy number. In Figure 1, the numbers *M = (l, u)* represent lower and upper values of the fuzzy number *M,* respectively, whereas *m* is the middle value of *M*.

Figure 1: *Triangular membership function.*



A fuzzy pattern is defined as a set of values of characteristics associated with a class of representation, which are immersed in an environmental uncertainty (Pedrycz, 1990). In the fuzzy logic literature, several pattern classification approaches have been proposed, such as fuzzy clustering (Pedrycz & Kwak, 2006), fuzzy pattern matching (Dubois et al., 1988), and fuzzy rules (Nozaki et al., 1988; Nguyen and Sugeno, 2012). In problems where the classes of patterns can be characterized by general relationship between entities, it becomes attractive to build classifiers based on fuzzy rules. In decision-making problems, fuzzy rule-based classification methods are especially useful for categorizing sets of alternatives according to their similarity (Duda et al, 2000; Osiro et al., 2014). Suppose that k patterns $x_p = (x_1^p, \dots, x_i^p, \dots, x_n^p)$, $p = 1,2, \dots, k$, with x_i^p defined in the continuum interval $[0,1]$, are given as training patterns from m classes: *Class 1 (C_1), Class 2 (C_2), …, Class t (C_t), …, Class m (C_m)*. In the context of supplier evaluation, x_p relates to a supplier performance pattern concerning n criteria used in the evaluation process. As for the classes, they relate to group suppliers with similar performance. The objective is to generate fuzzy rules that associate m classes with the patterns defined by x_p:

$$Rule\ r: IF\ \ x_1^p\ is\ A_1^r\ \ AND \dots AND\ \ x_n^p\ is\ A_n^r\ \ THEN\ \ x_p\ belongs\ to\ C^r\ with\ W = W^r \quad (10)$$

where r is the label of the fuzzy rule, A_i^r $(i = 1, 2, \dots, n)$ are fuzzy subsets in the unit interval $[0,1]$, C^r is the consequent, and W is the grade of certainty (or weight assigned to the rule). The value of C^r is defined by one of the m classes, according to the following equation (Ishibuchi et al., 1992; Osiro et al., 2014):

$$\beta_{Cr} = max(\beta_{C1}, \beta_{C2}, \dots, \beta_{Ct}, \dots, \beta_{Cm}) \quad (11)$$

where β_{Cr} indicates the largest compatibility grade of one of the m classes with the *r*th fuzzy rule. Assuming that a rule set S is given to form a fuzzy rule-based classification system, an unknown pattern $x_p = (x_1^p, \dots, x_i^p, \dots, x_n^p)$ can be classified by calculating α_{Cr} for *r = 1, …, m*

$$\alpha_{Cr} = max\left\{\sum_{i=1}^{m} \mu_{A_i^r}(x_i) W^r | C^r = C_t;\ r\epsilon S\right\}, \quad (12)$$

and classifying x_p in the class that maximizes α_{Cr}.

Fuzzy logic is especially useful when ambiguity and vagueness exist in the inputs. This is, for example, the case when the inputs rely on human perceptions. Systems requiring linguistic descriptions, as is often the case in supplier selection, are particularly well-suited to be modeled by fuzzy sets. In supplier selection problems, the main input is the decision-maker's perceived importance of certain criteria. However, this perceived importance is subjective, and one can therefore not obtain exact assessments for each attribute. Fuzzy set theory allows for qualitative expressions that are required to take subjectivity into account. Fuzzy logic has proven to be an excellent choice for many control system applications from small, hand-held products to large computerized process control systems.

The fuzzy inference system (FIS) is an optimization technique that uses fuzzy set theory to map inputs to outputs, based on certain rules. Both inputs and outputs are expressed in real (crisp) values, while the internal processing is based on fuzzy logic. A fuzzy inference system normally has several components and stages: the process starts with the fuzzification of inputs, which relates the numerical values of the crisp input variables to the values of the activated linguistic variables. The inference rules relate the levels of input variables to those of output variables. The most common fuzzy inference systems include *if…and/or…then* rules (Zimmermann, 1991). This is followed by aggregation where the fuzzy sets that represent the outputs of each rule are combined into a single fuzzy set. Finally, the defuzzification is performed by transforming the fuzzy variables back to crisp numbers via membership functions. The fuzzy inference system constructed to handle our green supplier selection problem is presented in the following section.

3.2 Fuzzy inference system using scikit-fuzzy

The fuzzy inference system in this work is built in Python and uses the scikit-fuzzy set of algorithms. This library contains all the elements of a typical fuzzy inference system, including construction of membership functions, construction of rules, and defuzzification. For this study, the inputs are the green attribute levels of the suppliers we want to evaluate. These values are defined on a Likert-scale, ranging from 0 to 10, and evaluated with a prespecified list of rules. After the evaluation of all the rules, the results are aggregated, and the model produces a supplier ranking defined on a 0 to 1 scale.

To explain all the steps of a fuzzy inference system, we have constructed a simple example in Figure 2 that presents the main components of model used in this study. This example illustrates the case with two attributes and five rules (however, the same components are also used for more complicated systems). The first step is to define the order of importance of the attributes. In this example, both attributes are assumed to have equal importance. The performance of only one supplier is evaluated. In the actual model, the decision-makers can add as many suppliers as needed.

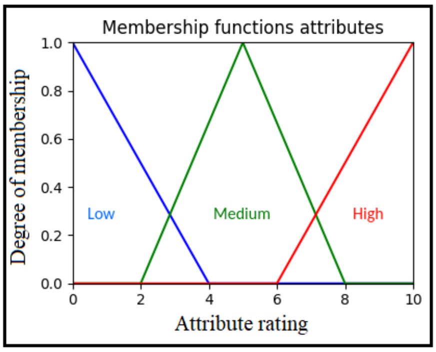
Figure 2: *Components of the fuzzy interference system. This figure shows a specific example with two attributes (pollution control and green manufacturing) and five rules*

Inputs and outputs of the fuzzy inference system

Input 1: Order of importance of attributes

Attribute order of importance	Attribute
1	Pollution control
2	Green manufacturing

Input 2: Shape of membership functions for attributes

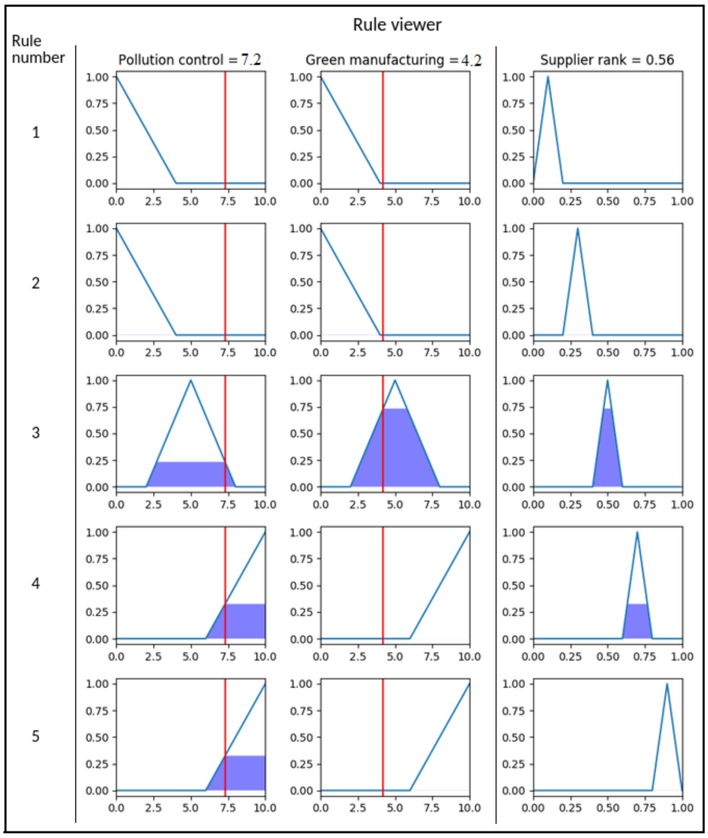


Input 3: Score per attribute for the supplier that is evaluated

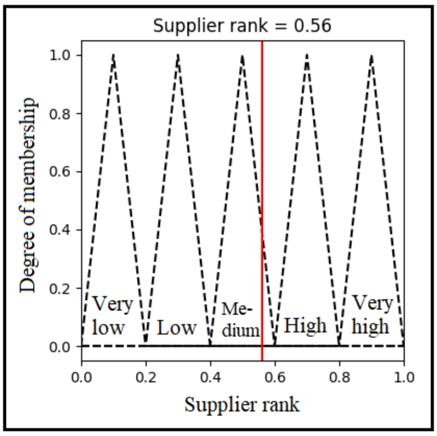
Attribute	Attribute rating
Pollution control	7.2
Green manufacturing	4.2

Input 4: Rule viewer evaluates the rules at the attribute ratings given in Input 3

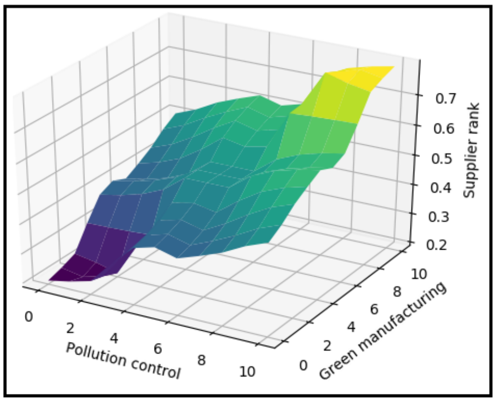
IF	Pollution control	low	AND	Green manufacturing	low	THEN	Supplier rank	very low
IF	Pollution control	low	OR	Green manufacturing	low	THEN	Supplier rank	low
IF	Pollution control	medium	OR	Green manufacturing	medium	THEN	Supplier rank	medium
IF	Pollution control	high	OR	Green manufacturing	high	THEN	Supplier rank	high
IF	Pollution control	high	AND	Green manufacturing	high	THEN	Supplier rank	very high



Output 1: Supplier rank



Output 2: Surface plot



Definition of importance order of the supplier attributes is followed by determination of the membership functions of these attributes and the membership functions of the output variables. These membership functions play a role in the 'fuzzification' of the crisp input values to fuzzy variables. In this example, the two attributes are described by triangular membership functions with three levels: 'low', 'medium', and 'high'. The output variable, supplier ranking, is described by a triangular membership function consisting of five levels: 'very low', 'low', 'medium', 'high', and 'very high'. These choices of the levels are based on recommendations from supplier selection literature (Ordoobadi, 2009; Paul, 2015). The membership functions in this example are similar to what has been used in the actual model. In order to be able to compare our work to previous studies of supplier selection we applied the membership functions that are most common in the literature: triangular, trapezoidal, and Gaussian (Osiro, et al., 2014; Hasan et al., 2015; Paul, 2015).

The third step of the input section includes those attribute levels of the supplier(s) that the decision-makers want to evaluate. This is an indication of how the suppliers of interest perform with respect to the chosen list of evaluation criteria. In the example in Figure 1, the supplier of interest scores 7.2 and 10 for the first and second attributes, respectively. The final input of this fuzzy inference system is the set of rules that connect the input variables to the final output, supplier ranking. The rules are normally constructed with the IF-THEN logic and include different fuzzy operators. In principle, each rule can be assigned a certain weight, which defines its impact on the final outcome. In this example, all the rules are assumed to have equal weight for simplicity. The rules can be visualized with the rule viewer, which will be discussed in detail in a later section. As part of the rule construction, two operators are defined to connect multiple antecedents. The OR operator is defined as the maximum of two antecedents. The AND operator is defined as the minimum of two antecedents. For each activated rule, the fuzzy inference system applies an implication relation between the fuzzy number resulting from the logic operations (AND or OR) on the antecedents and the consequents. Similar to most studies in the supplier selection literature, this model applies Larsen's product fuzzy implication relation (Lee, 1990).

The main result of the fuzzy interference system is the supplier ranking, which is defined on a scale from 0 to 1. The supplier ranking is calculated by aggregation of the results of all the rules. The fuzzy sets that represent the outputs of each rule are combined into a single fuzzy set. Aggregation normally occurs once for each output variable, prior to the last step, defuzzification. There is a variety of defuzzification methods available within the scikit-fuzzy program. Defuzzification is required to convert fuzzy outputs back to crisp numbers such as the supplier rank. In this work, we choose a subset of three defuzzification methods that are most commonly used in the literature. The bottom left panel of Figure 1 shows that the ranking index of the evaluated supplier with the mentioned attribute levels obtains the value 0.56 ('medium'). Additional outputs of the fuzzy inference system include surface maps of the supplier ranking as a function of the importance rating of supplier attributes (lower right panel of Figure 1). Based on this surface map, both attributes are almost equally important in the construction of the supplier ranking. The scikit fuzzy set of algorithms also allows to create more complex (e.g., four-dimensional) surface plots which allow to evaluate the impact of three different attributes simultaneously. Separate parts of the fuzzy inference system are described in more detail in the following sections.

4 Problem formulation

The construction of a fuzzy inference system starts with the identification of evaluation criteria, followed by the construction of separate constituent parts of the system. The following section discusses the elicitation of major environmental factors affecting supplier selection decision-making. Afterwards, the membership functions and rule construction methods are presented.

4.1 Green supplier attributes

In order to develop a comprehensive list of green supplier attributes that could be applicable in various supplier selection settings, we started with the existing academic and practitioner literature. This allowed us to create an initial list of attributes which we ran through several rounds of expert interviews. After interviewing more than ten experts from various industries (e.g., transport & logistics, consumer goods, healthcare, manufacturing), we adjusted the initial list in terms of not only content, but also design and wording. Our goal was to come up with a list of environmental criteria which are mutually exclusive and collectively exhaustive. At the same time, it was important to have attribute names which are intuitive and easily understandable for decision-makers. The final list of green supplier attributes is resented in Table 1. During the interviews, we also asked the respondents to rank the final list of attributes. The order of the attributes shown in Table 1 corresponds to the average relative importance, based on collected responses. Pollution control has the highest average importance rating, while green image is the least important attribute according to the interviewed industry experts. It is also very important to mention that while the constructed fuzzy model includes the predetermined list of supplier evaluation criteria and their importance rankings, the flexibility of the model allows each decision-maker to adjust the list and reshuffle the order. The last column of Table 1 shows the abbreviations that were used for each attribute in the fuzzy inference system.

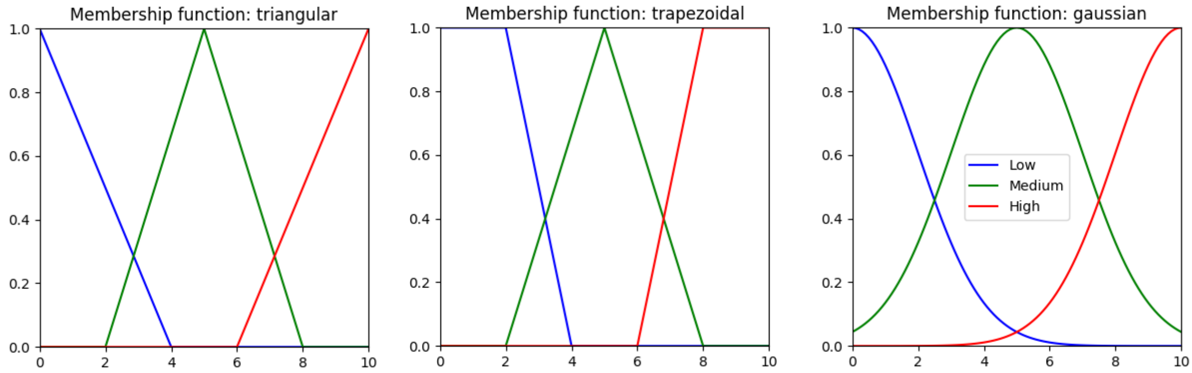
Table 1: *Green supplier evaluation and selection criteria (attributes).*

	Attribute name	Abbreviation
1	Pollution control	PC
2	Green manufacturing	GM
3	Green design	GD
4	Environmental management processes and systems	EMP
5	Green purchasing	GP
6	Green R&D investment	GRD
7	Green technology usage	GTU
8	Recycling rate	RR
9	Green certification (rating)	GC
10	Green image	GI

4.2 Membership functions

Three different membership functions were considered for the ten input variables (green supplier attributes) used in this study: triangular, trapezoidal, and Gaussian. These membership functions are visualized in Figure 3. The choice of membership functions was made based on recommendations in the fuzzy logic literature (Ordoobadi, 2009; Hasan et al., 2015). These membership functions (especially the triangular membership function) are considered to be relatively simple and perform better than other types (Ordoobadi, 2009; Sivamani et al., 2017). The triangular membership function is explained in detail earlier in this paper. In a trapezoidal membership function, the low and high levels are represented by trapezoidal membership functions, and the medium level is represented by a triangular membership function. As for the Gaussian membership functions, in this work we used Gaussians centered on 0, 5 and 10 with standard deviation of two, for the low, medium and high levels, respectively. Later in this paper, we apply different membership functions to the same supplier selection problem in order to check the robustness of our model. The membership function of the output variable, the supplier ranking, is kept fixed at the configuration shown in Figure 2. It includes five triangular membership functions without overlaps, which describe five possible supplier ranking levels.

Figure 3: *Membership functions that are available for the green attributes.*



4.3 Rule construction

Fuzzy rules are combinations of IF-THEN conditional statements supported by AND/OR logical operators. Fuzzy rules are often employed to capture the imprecise modes of reasoning that play an essential role in human assessments. In this fuzzy inference system of ten attributes, a total of 140 rules were constructed to relate different part of the system to each other. An example of a rule is: IF pollution control is high, AND green manufacturing is high, THEN supplier ranking is very high. Each rule is assigned a weight, which determines its impact on the final supplier ranking. Unlike the previous efforts of applying fuzzy logic to supplier selection, all the rules in this system are dynamic and change automatically, based on the importance ranking of supplier attributes, as assigned by decision-makers. This is one the most important contributions of this study. A rule viewer can be constructed in Python to demonstrate different rules and their impact on the final outcome. Figure 2 (right-hand side of the input section) presents the rule viewer for a simple numerical example.

Once all the rules have been evaluated based on fuzzy logic, the results are aggregated and defuzzified to find a crisp output value, supplier ranking index. Perhaps the most popular defuzzification method is the center of gravity (CoG)/centroid calculation, which provides a crisp value based on the center of gravity of the fuzzy set. The total area of the membership function distribution, used to represent the combined control action, is divided into a number of sub-areas. The area and the center of gravity (or centroid) of each sub-area is calculated and summed up across all the sub-areas to find the defuzzified value for a discrete fuzzy set (Saade and Diab, 2004). Several built-in methods, such as the centroid, bisector, middle of maximum (the average of the maximum values of the output set), largest of maximum and smallest of maximum, are supported within the scikit-fuzzy set of algorithms. We apply different defuzzification methods to the same example to check the robustness of our model in a later section.

5 Results and discussion

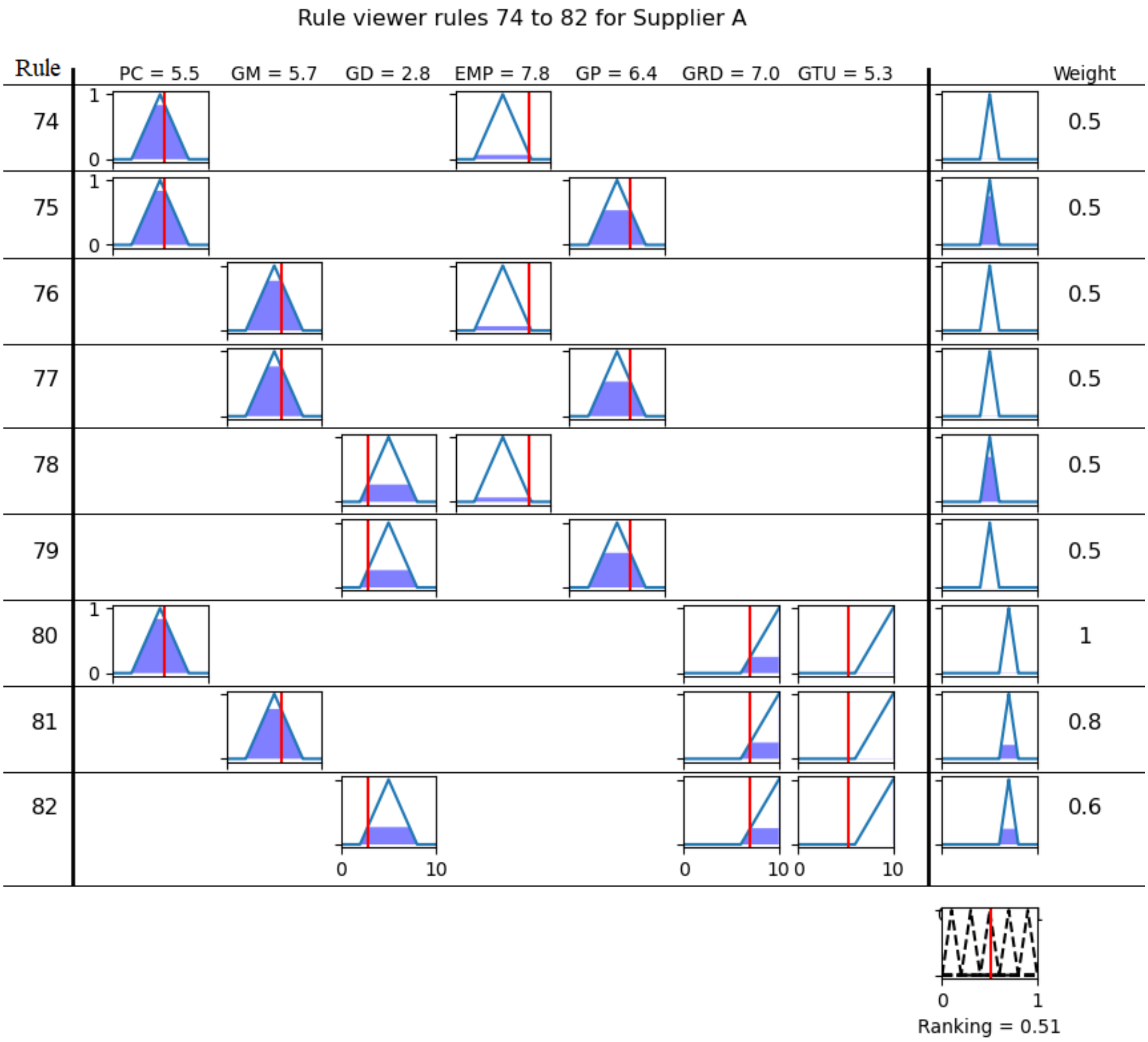
In order to discuss the outcomes of our fuzzy inference system, the proposed methodology was applied on a numerical example considering hypothetical data for three suppliers. The decision-makers are representatives of a hypothetical manufacturing company which purchases production materials from three different vendors. For simplicity, we assume that the decision-makers take the supplier attribute ranking and the constructed rules as given. Hence, the main input provided by the hypothetical decision-makers is their perception of the suppliers' performances with respect to the ten environmental selection criteria. As shown in Table 3, each supplier performs differently with respect to different criteria. The supplier profiles are entered in fuzzy inference system in order to run them through the constructed fuzzy rules and obtain a ranking index for each supplier.

Table 2: *Green attribute ratings for three suppliers.*

	PC	GM	GD	EMP	GP	GRD	GTU	RR	GC	GI
Supplier A	5.5	5.7	2.8	7.8	6.4	7.0	5.3	7.1	4.0	6.7
Supplier B	5.9	9.2	7.4	3.5	6.9	6.6	4.3	0.6	5.4	6.2
Supplier C	9.4	0.8	6.1	3.0	3.2	8.7	1.6	10.0	2.6	7.8

The rule viewer for Supplier A is shown in Figure 4 (this view includes rules 74-82 only). This rule viewer is constructed with triangular membership functions, and each row represents one rule. In this particular example, only those green attributes that play a role in each rule are shown. The red lines show the attribute value of Supplier A. The blue areas under the membership function represent the weights which activate the membership functions in a given rule. The figures in the last column show the output membership function activation. These degrees of membership are scaled with the subsequent weights which were assigned to each rule during the construction process. The plot in the right bottom corner of Figure 4 shows the aggregated and defuzzified result of all the rules (not just the subset shown in the figure), which becomes the value 0.51 for Supplier A.

Figure 4: *Rule viewer of a subset of 9 rules in the full model*



Note: These rules only describe six of the ten attributes. The empty columns have been cut out for simplicity.

The three hypothetical suppliers were evaluated based on three different membership functions defined in the previous section. As shown in Table 3, Supplier B has the highest ranking index independent of the applied system. Supplier A is the second best alternative, followed by Supplier C as the last option. This comparison between different membership functions was conducted in order to check the robustness of the proposed model.

Table 3: *Fuzzy inference results with three types of membership functions for three suppliers.*

	Triangular	**Trapezoidal**	**Gaussian**

Supplier A	II	0.51	II	0.51	II	0.53
Supplier B	I	0.57	I	0.60	I	0.57
Supplier C	III	0.48	III	0.44	III	0.48

Similarly, different defuzzification methods were applied to the same supplier evaluation problem to compare the resulting supplier ranking indices. While the standard defuzzification approach was the CoG/centroid method, bisector and mean of maximum (MoM) methods were also employed (van Leekwijck & Kerre, 1999). For simplicity, the membership functions were kept fixed at the triangular version. Table 4 shows the supplier rankings for the same set of three suppliers across different defuzzification methods. The consistency of these results also supports the applicability of the constructed model.

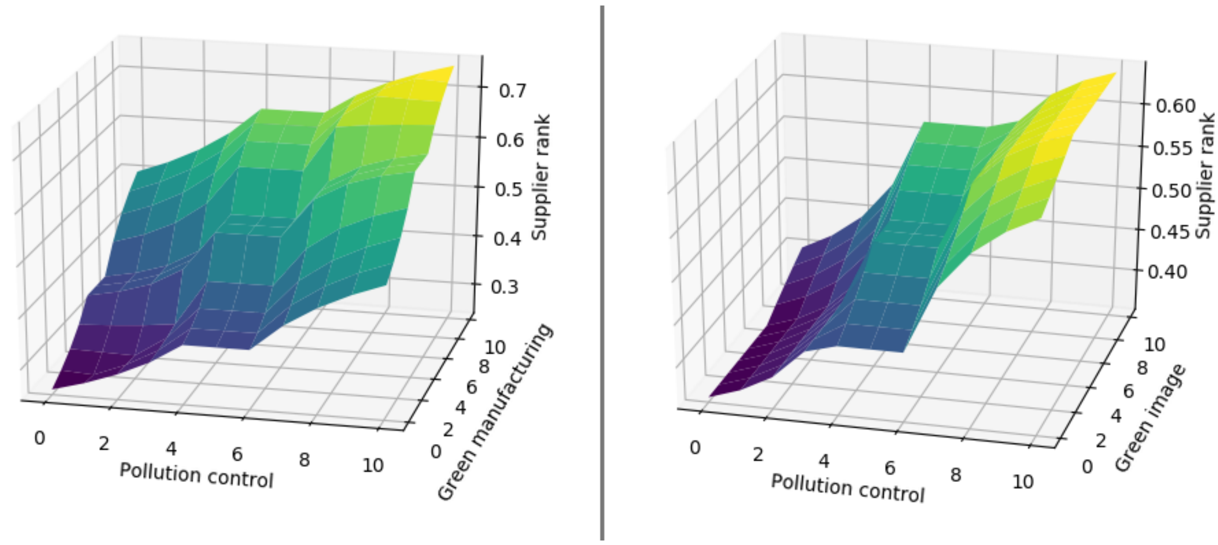
Table 4: *Fuzzy inference results with three types of defuzzification methods for three suppliers.*

	Centroid		**Bisector**		**MoM**	
Supplier A	II	0.51	II	0.51	I	0.70
Supplier B	I	0.57	I	0.55	I	0.70
Supplier C	III	0.48	III	0.49	III	0.50

Finally, more than 50 hypothetical scenarios were generated to test the robustness of the proposed fuzzy inference system. The model was able to provide consistent results for all the scenarios with different supplier profiles and application methods.

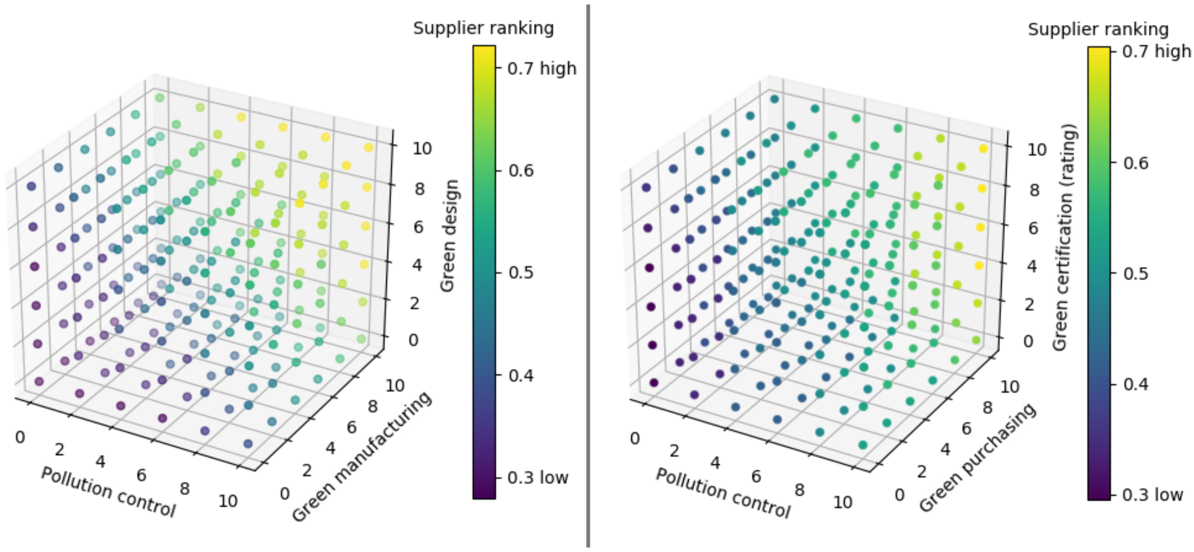
The constructed fuzzy inference system also allows to analyze the interdependencies between input and output variables. One can systematically vary two of the attributes to map out the supplier ranking for each combination. The resulting surface maps show how supplier ranking changes as we move from one input combination to another. Scikit-fuzzy allows to produce these as so called temperature maps in order to easily visualize the interdependencies. Figure 5 shows two of the three-dimensional surface plots generated in this fuzzy inference system. For simplicity, triangular membership functions and centroid defuzzification method were employed. The left-hand side shows the development of supplier ranking based on different combinations of pollution control and green manufacturing values. As shown in the figure, that these two environmental selection criteria have similar influence on the supplier ranking. The plot on the right-hand side shows the dynamic supplier rank as a function of pollution control and green image. One would expect for pollution control to have a larger influence on the supplier ranking, since this attribute was given more importance in the initial attribute relevance ranking (Table 1). As shown in the figure, supplier ranking changes drastically due to changes in pollution control, while green image has a negligible effect.

Figure 5: *3D surface plots of the supplier ranking (vertical direction) as function of the rating of two green supplier attributes.*



This fuzzy inference system allows the decision-makers to go even one step further and create four-dimensional surface plots. Examples of those 4D plots are given in Figure 6. The main advantage of such a visualization is that it allows the decision-makers to see simultaneous impact three different green attributes. In this case, pollution control, green manufacturing, and green design have roughly similar importance and effect on supplier ranking. For comparison, pollution control has significantly more relevance compared to green purchasing and green certification.

Figure 6: *4D surface plots of the supplier ranking (represented by the colors) as function of the rating of three green supplier attributes.*



This study provides a strong contribution to the literature of supplier selection due to its managerial implications while addressing the issue of uncertainty for green supply chain management. Today's business environment has forced the industries to focus on effective supply chain management in order to gain competitive advantage. With the growing worldwide awareness of environmental protection and the corresponding increase in regulations, green supplier selection has become an important lever for companies to gain environmental sustainability. A firm's environmental performance is not only related to its own environmental efforts, but also it is greatly affected by its suppliers' environmental performance and green image. During recent years, determining an appropriate supplier in the green supply chain has become a key strategic consideration. While there are objective criteria that need to be taken into account, there also exist a number of subjective factors affecting supplier selection. Subjectivity of evaluation information often invites vagueness and ambiguity in the decision-making, implying that exploration of fuzzy set theory may be beneficial. Industry management may explore this application of fuzzy set theory in suitable circumstances to promote effective supplier selection considering green perspectives (Ordoobadi, 2009; Sahu et al., 2016; Kiani Mavi, 2015).

The proposed methodology also contributes to the existing fuzzy logic literature (Kumar et al., 2011; Osiro, et al., 2014; Hasan et al., 2015; Paul, 2015). Unlike other approaches that combine fuzzy set theory with other decision support systems, the proposed fuzzy inference system is based on simple rules that capture the subjectivity of human reasoning. Furthermore, the number of suppliers that can be evaluated simultaneously is unlimited. This is a significant advantage of this model compared to other popular approaches in the supplier selection literature, such as analytical hierarchy process (AHP), analytical network process (ANP), fuzzy AHP, and fuzzy ANP. The Pythonic nature of the developed methodology also provides certain advantages over the traditional MATLAB-based fuzzy inference systems applied in the supplier selection literature. First and foremost, the constructed rules are dynamic, which allows the decision-makers to significantly expedite the supplier evaluation process. The only required input is the decision-maker's perception of how the evaluated suppliers perform with respect to the green selection criteria. In addition, the flexibility of the model allows for adjusting the list and the importance ranking of green attributes, as well as constructing additional rules or changing existing ones.

6 Conclusions and future work

Selection of appropriate suppliers is one of the most important stages of supply chain management as it ensures sound and smooth production process. Supplier categorization, selection, and performance evaluation have strategic importance to companies. Global competition, mass customization, high customer expectations, and continuously changing economic conditions force companies to heavily rely on external vendors and outsource a significant portion of their activities. Companies now have to manage a growing network of processes and functions that were previously controlled internally. Furthermore, with the increasing public awareness of environmental issues and constant regulatory pressure, many firms design their supply chain management processes in accordance with existing environmental requirements. Green supply chain management (GSCM) is considered an effective practice to improve environmental performance throughout the entire supply chain. As part of the GSCM, effective green supplier selection can help firms decrease the environmental and legal risks and increase their market competitiveness. Generally, supplier evaluation and selection is a highly complex decision-making problem which requires a trade-off between multiple criteria exhibiting vagueness and imprecision. With the incorporation of the environmental component, it becomes even more challenging and involves higher risks.

In this study, a fuzzy logic approach was proposed to help decision-makers deal with the uncertainty and vagueness of supplier evaluation and selection, purely based on environmental criteria. First, a comprehensive list of green supplier selection criteria was prepared based on literature review and several rounds of expert interviews. Afterwards, a

Pythonic fuzzy inference system was constructed which uses the importance ranking of green supplier evaluation criteria as input and allows decision-makers to evaluate an unlimited number suppliers simultaneously. This is a significant advantage of the proposed model over the alternative decision support studies which normally work for a limited number of suppliers only. The main output of this model includes the supplier ranking indices for all the evaluated suppliers. The constructed 140 rules were verified and validated with the help of three- and four-dimensional surface plots. The developed model was presented on a numerical example considering hypothetical suppliers. The methodology was also tested using various supplier comparison scenarios, as well as different membership functions and defuzzification methods. Finally, the flexibility of the proposed model makes it an optimal tool to assist practitioners in capturing the uncertainty of decision-making and accommodate their individual preferences of green supplier selection. This paper contributes to the supplier selection literature due to its ability to account for vagueness and subjectivity in green supply chain management. It also provides an optimal tool for practitioners to improve green supplier selection decision-making.

A limitation of this model is the fixed number of environmental criteria. Given that the starting point of this study was to identify and analyze the relevant green supplier attributes, we decided to maintain a fixed list of ten attributes and allow the decision-makers to change the importance ranking based on their individual preferences. Future studies could develop this model further by allowing different users to add new attributes or remove existing ones depending on their particular industry setup. Another improvement would be to assist decision-makers not only in supplier selection, but also order allocation. This would help them decide on the optimal level of ordered items from each selected supplier. Finally, this model was tested on numerous hypothetical supplier selection scenarios (one of which is presented in this paper), which confirmed its robustness and applicability. At the same time, it would be helpful to apply it on a real-life case, e.g., the purchasing division of a manufacturing or servicing company.

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