INTEGRATED FANP-F-MIGP MODEL FOR SUPPLIER SELECTION IN THE RENEWABLE ENERGY SECTOR

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Abstract. The available integrated models for choosing efficient suppliers developed so far are mostly specific to companies with mass production capabilities. However, in some sectors involved in project-type manufacturing, the same decision-making criteria cannot be applied and, plus, there is no point in determining the quantity of orders. For instance, in wind power plant projects, a single turbine supplier needs to be selected for each project. This study proposes an integrated FANP-f-MIGP model that ensures the selection of the optimal supplier for each project by applying the model to an energy firm. The criteria specific to the selection of wind power plant turbine suppliers are established, and the criteria weights are obtained by fuzzy analytic network process (FANP). As a result of the analysis, the most important criterion of all is cost. These weights constitute the coefficients of the f-MIGP model's objective function. Under the defined constraints, by minimizing cost and risk and maximizing quality and services of the firm, the selection of an optimal wind turbine supplier from three suppliers for each of three projects is ensured. This study contributes to the literature both by the specific criteria it establishes and its proposed integrated model which allows for the selection of the best supplier in wind turbine and similar project-based productions.

Keywords: supplier selection, project-type manufacturing, fuzzy analytic network process, fuzzy mixed integer goal programming, renewable energy sector, wind power plant.

JEL Classification C44, C61, D81, D22, M11, Q49.

Introduction and background

Selection of the supplier has been a very important issue focused upon by academicians and decision-makers lately. The decision-making process that allows for effective evaluation of suppliers has a very complex structure. This is because the evaluation process includes many aspects that examine the performances of suppliers and the conditions for long-term cooperation with them (Zhang *et al.* 2012). Nowadays, the relation between manufacturer and supplier is not only about trade relations anymore; it also means partnerships that constitute competitive advantages (Sheth, Sharma 1997). Supplier management is the ability to have a long-term relationship with suppliers and to

use fewer but trustworthy suppliers. Therefore, selecting the correct supplier requires choosing from a wide array of factors including both qualitative and quantitative elements, rather than simply browsing the price list (Ho *et al.* 2010). Supplier selection, too, involves a decision-making process with the same requirements.

Techniques such as Multi-Criteria Decision-Making (MCDM), Mathematical Programming (MP) and Artificial Intelligence (AI) have been extensively used in the literature. In some supplier selection problems, one-stage analyses are used, while others prefer two-stage integrated methods. Some of the studies that adopt the one-stage analysis method are as follows: AHP (Chan 2003; Kar, Pani 2014; Dweiri *et al.* 2016), FAHP (Mızrak Özfirat *et al.* 2014; Lo, Sudjatmika 2016), FTOPSIS (Boran *et al.* 2009; Roshandel *et al.* 2013; Dowlatshahi *et al.* 2015), ANP and FANP (Tseng *et al.* 2009; Kang *et al.* 2012; Razmi *et al.* 2009), DEA (Weber, Desai 1996; Braglia, Petroni 2000), MOP (Feng *et al.* 2011; Arikan 2013), LP (Ng 2008), GP (Ding *et al.* 2005; Lin, Yeh 2010; Jadidi *et al.* 2015), f-MIGP and f-MILP (Kumar *et al.* 2004; Bohner, Minner 2017).

In the two-stage methods within the literature, supplier selection is performed using two or more methods together. As in the present study, other works that have used MCDM in the first stage and MP in the second stage can be summarized as follows: Perçin (2006), in his study where he integrated analytic hierarchy process (AHP) and multi-objective pre-emptive goal programming (PGP) methods, conducted a supplier selection for a company that operates in the automotive sector and determined the order quantity. Çebi and Bayraktar (2003) answered the question as to which suppliers the eight raw materials for a food company should be procured by integrating the lexicographic goal programming (LGP) and AHP methods. Kasirian *et al.* (2010) found the priorities of suppliers in an application they conducted for an automotive company by using AHP and analytic network process (ANP). In the second stage, they determined two goals, namely maximizing the total value of purchase and minimizing the total cost of purchasing, achieved the goals with PGP, and then compared the results from each method. Ku *et al.* (2010) integrated the fuzzy analytic hierarchy process and fuzzy goal programming (FAHP-FGP) models for global supplier selection and conducted a study indicating how many products should be purchased from the proper ones among the thousands of suppliers. Similarly, Nikou and Moschuris (2016) combined AHP and GP models to select suppliers for the defense industry. The authors calculated the scores of four suppliers selected for the three products purchased by the Department of Defense with the AHP method and ensured the distribution of the ordered amounts to the suppliers in a manner that will use financial resources optimally with the help of GP. Liao and Kao (2010) integrated the Taguchi loss function, AHP and multi-choice GP methods and presented a theoretical study for supplier selection. After determining the optimal suppliers by AHP, Ghodsypour and O'Brien (1998) and Lin *et al.* (2011) calculated the optimal quantities to be purchased from each supplier by LP so as to minimize costs. By utilizing the Fuzzy MULTIMOORA technique, Çebi and Otay (2016) assessed suppliers, selected three out of five among them and, later in the second stage, determined the optimal order amount to be assigned to these suppliers using FGP. In the same way, Ayhan and Kilic (2015) first obtained the weights of four criteria for five products us-

ing F-AHP and, in the second stage by using these weights in the Mixed Integer Linear Programming (MILP) model, distributed the ordered amounts among six suppliers. Jolai *et al.* (2011) and Damghani *et al.* (2013) selected appropriate suppliers by using TOPSIS in the first stage and FGP in the second. Huang and Hu (2013) integrated the FANP-GP and De Novo Programming (DNP) methods in Taiwan automotive sector and implemented a two-stage supplier selection. In the first stage, they determined the optimal order quantity to be purchased from the best supplier using FANP-GP; later, they set the source limitations and capacities by DNP and minimized the purchasing budget. Luangpantao and Chiadamrong (2015) proposed a multi-objective linear supplier selection model that reflects the imprecision and risks in the decision-making process. Illustrating their model, they proposed with an example the criteria and supplier weights using F-TOPSIS in the first stage; next, they tested more than one Fuzzy LP model. Kavitha and Vijayalakshmi (2013) obtained the weights of supplier selection criteria by AHP and sorted the suppliers by TOPSIS. Later, they determined the order amounts by Fuzzy Multi Objective Linear Programming (FMOLP). Gupta *et al.* (2016) proposed an optimization model integrating the fuzzy multi-objective integer linear programming (FMOILP) and AHP models for supplier selection and order allocation problems and applied the model to an Indian firm in automotive sector, designing and producing auto parts.

Although there is not a similar supplier selection study in the renewable energy sector in which the approach by the present paper is also applied, certain studies could be found where MCDM and MP models are employed for several reasons. Heo *et al.* (2010), for instance, weighed the required criteria for an effective dissemination program in the renewable energy sector using FAHP. Akash *et al.* (1999) selected the most optimal one among different electricity production resources using AHP; Chen *et al.* (2010) selected the most optimal one among a number of solar-wind power generation projects with the help of FAHP; and Lee *et al.* (2009) decided on the most optimal wind farm project in terms of main criteria, benefits, opportunities, costs and risks with a new AHP-based MCDM. Cristobal (2012) and Chang (2015) implemented GP application in order to determine the optimal plant type and location. In order to find the optimal renewable energy source, Büyükozkan and Güleryüz (2016) used DEMATEL-ANP integrated model and for finding optimal renewable energy project, Yazdani-Chamzini *et al.* (2013) used the COPRAS-AHP integrated model. Shafiee (2015) determined the most suitable risk mitigation strategy for off-shore wind farms using FANP. In turn, Akbari *et al.* (2017) suggested the most appropriate facility location for off-shore wind farms using AHP and FANP. In the same field of off-shore wind farms, Fetanat and Khorasaninejad (2015) came up with an integrated F-DEMATEL and F-ELECTRE. While Şengül *et al.* (2015) addressed the issue of renewable energy supply systems in Turkey using the F-TOPSIS method, Tahri *et al.* (2015) calculated the weights of the criteria used to determine the location of solar farms using the AHP method. Ghosh *et al.* (2016) obtained the importance weights for the energy produced from ocean waves as a renewable energy source using AHP, and determined the suitable location with an index established based on the ANN method.

As summarized above, studies conducted on the supplier selection usually deal with the selection of suppliers in mass production and usually measure the criteria weights in the first stage and determine the order amount to be procured from each supplier in the second. On the other hand, in wind power plant projects, usually there is a need to work with a single turbine supplier and it is not possible to divide the order quantity between suppliers. The selection of wind turbine supplier is a process with an uncertain structure that includes both the qualitative and quantitative data together as in the other sectors. In these projects, it is quite a challenge for administrators to determine the weights of the objective function. Besides, energy firms may implement simultaneous or consecutive projects with high budgets and long life-span. In such a case; in order to minimize the losses that might arise from changing circumstances, prices and possible conflicts, companies have to work with efficient and accurate suppliers.

Due to such reasons, the present paper carries out the selection of an optimal supplier for each wind power plant project using an integrated fuzzy analytic network process and fuzzy mixed integer goal programming (FANP-f-MIGP) model. The first aim of the study is to determine the specific criteria for wind turbine supplier selection and to develop a supplier selection model that uses these criteria as a base. The second aim is to explain how an integrated FANP-f-MIGP model can be used to determine the optimal wind turbine supplier by minimizing the cost and risk of suppliers and maximizing quality and services.

The present study involves two stages. In the first stage, wind turbine supplier selection criteria are determined by FANP and their weights are obtained. ANP method is an extended version of AHP and it is preferred in the analysis of complex systems. It is not possible to measure the qualitative factors completely because of the undetermined structure of decision-makers. Therefore, using fuzzy numbers instead of crisp numbers for the measurement of qualitative factors yields more realistic results. Within this context, using FANP is preferred to calculate the weights of the criteria as well as the sub criteria. The proposed model serves two purposes: the imprecision due to personal judgments are better reflected and, thanks to the established network structure, the interdependencies of these decisions can be expressed.

In the second stage, under the constraints defined and the objective function where the criteria weight acquired by FANP are used, the selection of an optimal wind turbine supplier for each wind power plant project is attained. The f-MIGP model is preferred for the solution of this multi-objective problem. Therefore, by considering the linguistic priorities of the decision-makers, a chance to define an imprecise aspiration level for each aim is provided.

The rest of this paper is organized as follows. In the first section, the procedures of FANP-f-MIGP model suggested for wind turbine supplier selection are introduced, and then FANP and f-MIGP models are mentioned. In the second section, the integrated model is applied to the energy firm. In the first stage of the application, supplier selection criteria are specified, FANP model is structured and criteria weights are calculated. In the second stage, optimal suppliers are selected by establishing the f-MIGP model. The last section contains conclusions and future work.

1. Methodology

1.1. Proposed procedure

This article suggests an integrated FANP-f-MIGP model for the selection of wind turbine supplier. The integrated FANP-f-MIGP procedure, which is used in selecting wind turbine supplier, is presented in Figure 1. In this model, FANP is used to find out the relative weights of supplier selection criteria; then, by taking these weights as the parameters of the objective function of f-MIGP model, the optimal supplier is determined for each project.

In the first stage of the proposed integrated model, FANP is used to obtain the weights of the wind turbine supplier selection criteria. The model embodies the five steps listed below:

Step 1: Wind turbine supplier selection criteria of decision maker are identified.

Step 2: The ANP model is structured by its goal, factors and sub-factors determined in the previous step.

Step 3: Pairwise comparison matrices are formed by the decision committee using the scale given in Table 2.

Step 4: The local and global weights of factors and sub-factors are calculated by Chang's extent analysis method (Chang 1996).

Step 5: The weights for main goals (cost, quality, service, risk) are determined in accordance with the obtained weight values.

In the second stage, the suppliers are evaluated by f-MIGP model and the optimal supplier for each wind power plant project of the firm is allocated. This process also includes five steps as follows:

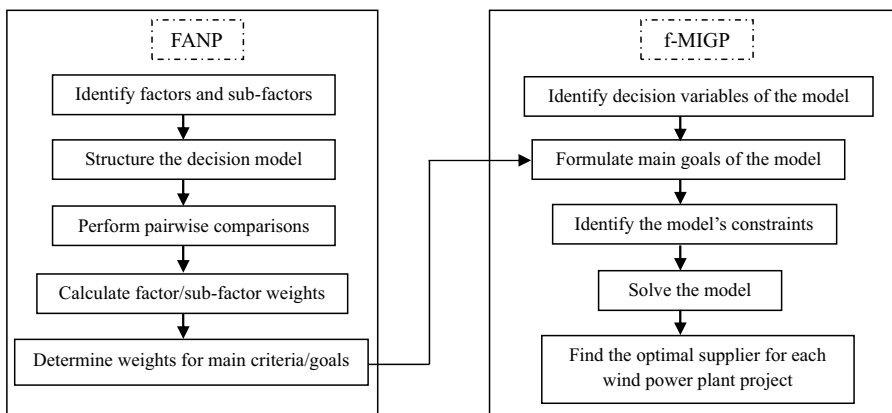*Step 1*: Decision variables for each supplier and project are identified.

Fig.1. An integrated FANP-f-MIGP procedure for wind turbine supplier selection

Step 2: By using the obtained weights in the first stage, the main goals of f-MIGP model are formulated. The main goals are cost minimization, quality maximization, service maximization and risk minimization.

Step 3: Turbine supplier selection constraints of the decision maker for wind power plant projects are identified.

Step 4: f-MIGP model is solved which evaluates each possible supplier for each project based on achieving the main goals under determined constraints.

Step 5: The optimal supplier for each wind power plant project is filtered.

1.2. Fuzzy analytic network process (FANP)

The Analytic network process (ANP) is a multi-criteria decision-making (MCDM) method which is developed by Saaty (1996). ANP is a generalization of the AHP, which was proposed by Saaty in 1980. The AHP method defines a one-dimensional hierarchical relationship between the criteria, sub criteria and alternatives. However, such a hierarchical structure cannot be applied to many real-life problems due to the interaction between its criteria (Saaty, Takizawa 1986; Saaty 1996). On the other hand, ANP evaluates a multi-dimensional dynamic relationship among the factors with the network structure it devises. The ANP method provides an opportunity for interaction and feedback both within and between the factors. Such feedbacks are more useful in more complex models that may involve uncertainty and risk (Meade, Sarkis 1999). While ANP, unlike AHP, does not require an independence assumption among the criteria, it uses a network structure that reflects all possible dependencies among those criteria, thus enabling ANP to provide more realistic results.

Pairwise comparisons in conventional ANP are inadequate to reflect the actual opinions of the decision-makers because such opinions have uncertainties. Both AHP and ANP techniques use pair-wise comparison of the criteria and sub-criteria in weighing the alternatives. Due to the uncertainty that exists in personal judgments and opinions, it is rather challenging to thoroughly reflect the decision-makers' opinions in these matrices and come up with a clear assessment (Özceylan *et al.* 2016). If these personal judgments are represented only with a fuzzy number range instead of a crisp number, the model can easily reflect the imprecision underlying the problems. For this purpose, using fuzzy linguistic variables, verbal statements have to be converted into numeric values. Otherwise, the entire decision-making process will be affected and satisfactory outcomes cannot be reached (Shafiee 2015). Therefore, in the decision-making processes of uncertain structures that include several external factors and rely on human judgment, FANP should be used instead of ANP.

Fuzzy logic was first introduced by Zadeh (1965) and is still used in order to define and solve the uncertainty and imprecision inherent in real-life problems. Using fuzzy values in such cases may result in more reliable results with reduced vagueness and

complexity. The difficulty in obtaining precise and comprehensive determination of perception through crisp numbers results in employing fuzzy numbers and linguistic variables to have a more reliable insight into the way individuals think (Erdoğan Aktan, Kaya Samut 2013).

In this study, by taking into account the interdependence and inner dependence of the criteria and sub-criteria in the network diagram built by FANP, more efficient and realistic solutions are sought with the help of linguistic variables as to the supplier selection problem that includes uncertain characteristics.

In evaluating fuzzy pair-wise comparisons, Chang's extent analysis method is employed in this study. Chang's extent method is validly used in the literature mostly because of its ease of application (Kahraman *et al.* 2006; Dagdeviren *et al.* 2008; Razmi *et al.* 2009; Moalagh, Ravasan 2013).

Let $X = \{x_1, x_2, \ldots, x_n\}$ be an object set and $G = \{g_1, g_2, \ldots, g_m\}$ be a goal set. According to Chang's approach, each object is taken and an extent analysis for each goal, g_i, is performed, respectively. Thus, m extent analysis values for each object can be obtained with the following symbols:

$$M_{gi}^1, M_{gi}^2, \cdots, M_{gi}^m, \ \ i = 1, 2, \cdots, n, \tag{1}$$

where all the $M_{gi}^1 \left(j = 1, 2, \cdots, m \right)$ are triangular fuzzy numbers (TFNs). The steps of Chang's extent analysis can be given as below:

Step 1: The value of fuzzy synthetic extent with respect to the *i*th object is defined as:

$$S_i = \sum_{j=1}^{m} M_{gi}^j \otimes \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^j \right]^{-1}. \tag{2}$$

To obtain $\sum_{j=1}^{m} M_{gi}^j$, perform the fuzzy addition operation of m extent analysis values for a particular matrix, such that:

$$\sum_{j=1}^{m} M_{gi}^j = \left(\sum_{j=1}^{m} l_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} u_j \right). \tag{3}$$

To obtain $\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^j \right]^{-1}$, perform the fuzzy additional operation of $M_{gi}^j \left(j = 1, 2, \cdots, m \right)$ values, such that:

$$\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^j \right] = \left(\sum_{i=1}^{n} l_i, \sum_{i=1}^{n} m_i, \sum_{i=1}^{n} u_i \right). \tag{4}$$

Then, compute the inverse of the vector in Equation 4 as

$$\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^j \right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} u_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} l_i} \right). \tag{5}$$

Step 2: The degree of possibility of $M_2 = (l_2, m_2, u_2) \geq M_1 = (l_1, m_1, u_1)$ is defined as:

$$V(M_2 \geq M_1) = hgt(M_1 \cap M_2) = \mu_{M_2}(d) = f(x) = \begin{cases} 1, & \text{if } m_2 \geq m_1 \\ 0, & \text{if } l_1 \geq u_2 \\ \dfrac{l_1 - u_2}{(m_2 - u_2) - (m_1 - u_1)}, & \text{otherwise} \end{cases},$$

(6)

where d is the ordinate of the highest intersection point D between μ_{M_1} and μ_{M_2}, and $hgt(M_1 \cap M_2)$ is a separation index for two fuzzy numbers. To compare M_1 and M_2, both $V(M_1 \geq M_2)$ and $V(M_2 \geq M_1)$ values are needed. The intersection between M_1 and M_2 is seen in Figure 2.
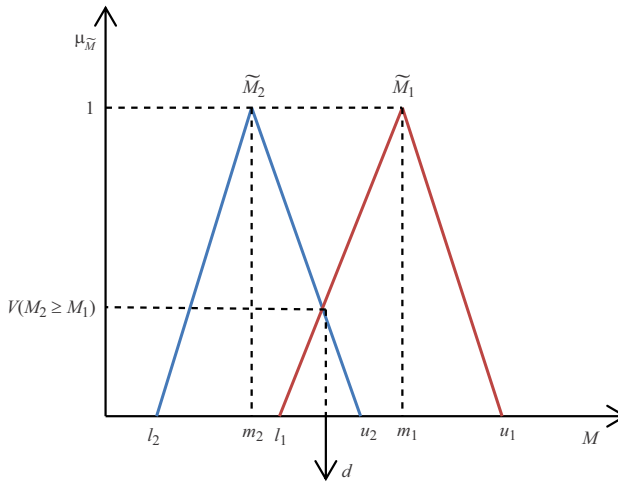

Fig. 2. The intersection between M_1 and M_2

Step 3: The degree possibility for a convex fuzzy number to be greater than k convex fuzzy numbers, $M_i (i = 1, 2, \cdots, k)$ can be defined by

$$V(M \geq M_1, M_2, \cdots, M_k) = V[(M \geq M_1) \wedge (M \geq M_2) \wedge \cdots \wedge (M \geq M_k)],$$
$$= \min V(M \geq M_i), \quad i = 1, 2, \cdots, k.$$

(7)

Assume that

$$d'(A_i) = \min V(S_i \geq S_k),$$

(8)

for $k = 1, 2, \cdots, n; k \neq i$. Then, the weight vector is given by

$$W' = (d'(A_1), d'(A_2), \cdots, d'(A_n))^T,$$

(9)

where $A_i (i = 1, 2, \cdots, k)$ are n elements.

Step 4: Using normalization, the normalized weight vectors are

$$W' = \left(d(A_1), d(A_2), \cdots, d(A_n) \right)^T,$$

(10)

where W is a non-fuzzy number.

1.3. Fuzzy mixed integer goal programming model (f-MIGP)

The problem of supplier selection is a decision-making problem that includes several goals, constraints and criteria. The traditional GP model, which is a multi-goal decision-making approach, was first applied by Charnes and Cooper (1961). GP models minimize the deviation of goal values from the aspiration levels. In this approach, decision-makers need to define a precise aspiration level for each goal; yet, the necessary information for supplier selection process also involves uncertainty. By providing the decision-makers an opportunity to define an imprecise aspiration level, the fuzzy logic helps to reach more appropriate results, especially in large-scale problems. Zimmerman (1978) has defined membership functions for fuzzy linear programming and presented a fuzzy optimization technique for LP problems. Narasimhan (1980), on the other hand, using linear membership functions, suggested an FGP model in which fuzzy goals determine imprecise aspiration levels.

In the present study, multi-goal supplier selection is done with the help of an f-MIGP model, with the mathematical formula as follows:

$$\begin{aligned}
&\text{Max } \lambda \\
&\text{Subject to} \\
&\lambda - \mu_k \left(f_k(x_i) \right) \leq 0, \ k = 1, 2, \cdots, n; \\
&s_j(x_i) \leq a_j, \ j = 1, 2, \ldots, J; \\
&h_l(x_i) = b_l, \ l = 1, 2, \ldots, L; \\
&x_i \geq 0 \ \text{and integer,}
\end{aligned}$$

(11)

where λ is the extra-continuous variable and $f_x(X)$ is the linear function of the kth objective.

In the formulation, x_i are n decision variables, s_j are the inequality constraints and h_l are the equality constraints. a_j and b_l are the right hand side constants for inequality and equality relationships, respectively.

A triangular membership function is employed to define fuzzy goals. The fuzzy membership functions of kth objective, $\mu_k \left(f_k(X) \right)$, are expressed as follows:

$$\mu_k \left(f_k(X) \right) = \begin{cases} 1, & \text{if } f_k(X) \geq g_k, \\ \dfrac{\left(f_k(X) - l_k \right)}{g_k - l_k}, & \text{if } l_k < f_k(X) < g_k, \ \text{for } f_k(X) \gtrsim g_k; \\ 0, & \text{if } f_k(X) \leq l_k \end{cases}$$

(12)

$$\mu_k\left(f_k\left(X\right)\right) = \begin{cases} 1, & \text{if } f_k\left(X\right) \le g_k, \\ \dfrac{\left(u_k - f_k\left(X\right)\right)}{u_k - g_k}, & \text{if } g_k < f_k\left(X\right) < u_k, \text{ for } f_k\left(X\right) \precsim g_k . \\ 0, & \text{if } f_k\left(X\right) \ge u_k \end{cases} \quad (13)$$

where l_k and u_k are respectively, the lower and upper limits for the kth goal. In the model, while the symbol " $\succsim$ " denotes the kth fuzzy goal approximately being greater than or equal to aspiration level g_k, the symbol " $\precsim$ " indicates being less than or equal to g_k.

2. Result

This case study for the application of an integrated FANP-f-MIGP model is conducted in 2015 in an engineering company in Ankara, Turkey, specialized in renewable energy projects. The study aimed to select an optimal wind turbine supplier for each of the three different wind power plant projects located in different regions and intended to use different types of wind turbines. In wind power plant projects, turbine suppliers not only procure turbines, but they are also liable for the transportation of turbines all the way to their installation and operation. In the study, a network model based on the determined selection criteria of turbine suppliers specific to wind power plants is developed, and the criteria weights are obtained by FANP. Then, an optimal supplier is assigned for each project with the help of the f-MGIP model. All of this process is executed with the decision-making team of the energy department of the company consisting of three individuals. This three-person team, consisting of the manager, the coordinator and the planning engineer, supervise the company's project.

2.1. FANP model for wind turbine supplier selection

Wind turbine supplier selection criteria
To determine the selection criteria for wind turbine suppliers, an extensive list of supplier selection criteria is prepared using the related literature (Liu, Hai 2005; Ku *et al.* 2010; Tam, Tummala 2001). As stated before, this list was submitted to the decision-making team in the energy department which was asked to determine the criteria in order to select the best suppliers. The team agreed on a total of 17 sub-criteria, grouped into four main criteria as: Cost (C1), Quality (C2), Service (C3) and Risk (C4), as in Table 1.

Structure of FANP model for wind turbine supplier selection
The FANP model devised to weight the selection criteria of wind turbine supplier is seen in Figure 3. At the first stage of the model, the objective; and at second and third stages the criteria and sub-criteria as in Table 1 are given.

The curves in the second stage indicate the inner-dependencies between the criteria. As a result, the approach allows the analysis of the effects of the models on each other.

Table 1. Descriptions of criteria and sub-criteria

Cost (*C1*):	
Product price (C11) :	Final price of the turbines including installation and warranty
Maintenance cost (C12):	Maintenance cost of the turbines upon warranty expirations
Spare parts cost (C13):	Cost of spare parts excluded from scope of warranty and upon its expiration
Payment terms (C14):	Customer payments on due dates
Quality (*C2*):	
Quality assurance (C21):	Quality control team of the suppliers implementing and monitoring quality issues
Problem-solving capability (C22):	Suppliers' ability to solve quality problems detected by customers
Product quality (C23):	Turbine production efficiency, material type and design
Rejection rate (C24):	Rate of damaged or non-functional components of the turbines
Service (*C3*):	
On-time delivery (C31):	Delivery of the components on due dates
Technical support (C32):	On-time action of the turbines technical support team of the suppliers in case of any breakdowns
Response to changes (C33):	Supplier's ability to respond changes depending on customer's demand, structure of the price, frequency of order and scenario of the current business
Warranties (C34):	Length of warranty period and its scope
Risk (*C4*):	
Concept conflict (C41):	Conflicts that may occur between the customer and the supplier due to past partnerships
Geographical location (C42):	Location of the plant and the possibility of natural calamities affecting the supply of the components
Political stability (C43):	Political stability of the supplier's country and its economic policies
Financial stability (C44):	Financial status of the supplier based on its history
Foreign exchange rate (C45):	Currency fluctuations during the payment period which may effect the customer

Weights of wind turbine supplier selection criteria

In this section, the weights of the criteria and sub-criteria in the network model are calculated. The pairwise comparison matrices related with the criteria is obtained through a questionnaire distributed to the decision-making team. To obtain the matrices, a linguistic scale for importance is used in Table 2 as defined by Kahraman *et al.* (2006).

The pairwise comparison matrices are analysed with the help of Chang's extent analysis method, and the local weights of the main criteria and their sub-criteria are calculated (see Table 3–7).
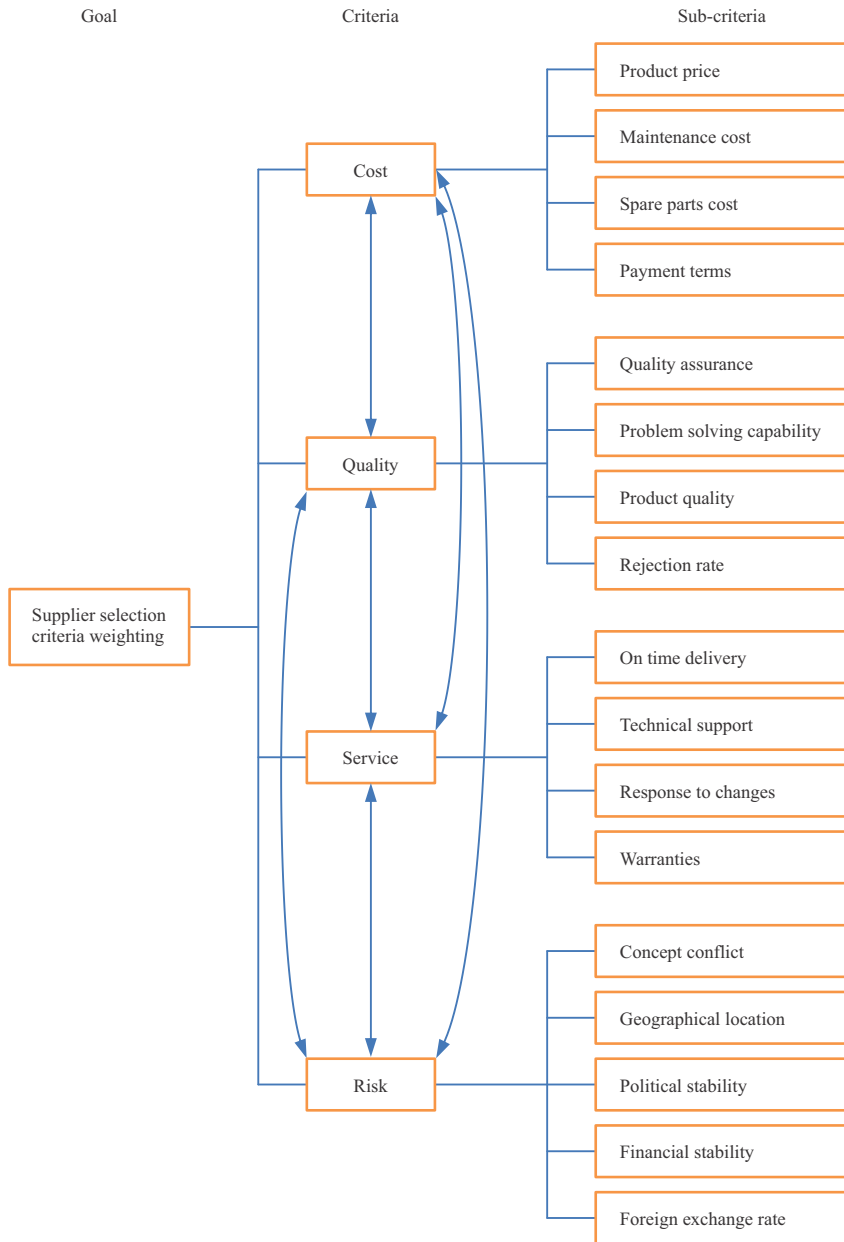
Goal	Criteria	Sub-criteria

Fig. 3. ANP model to weight supplier selection criteria

Table 2. Linguistic scale for importance

Linguistic scale for importance	Tringular fuzzy scale	Tringular reciprocal fuzzy scale
Just equal (JE)	(1, 1, 1)	(1, 1, 1)
Equally important (EI)	(1/2, 1, 3/2)	(2/3, 1, 2)
Weakly more important (WMI)	(1, 3/2, 2)	(1/2, 2/3, 1)
Strongly more important (SMI)	(3/2, 2, 5/2)	(2/5, 1/2, 2/3)
Very strongly more important (VSMI)	(2, 5/2, 3)	(1/3, 2/5, 1/2)
Absolutely more important (AMI)	(5/2, 3, 7/2)	(2/7, 1/3, 2/5)

Table 3. Local weights and pairwise comparison matrix of main criteria

Criteria	C1	C2	C3	C4	Weights
Cost (C1)	JE	WMI	VSMI	SMI	0.48
Quality (C2)		JE	SMI	WMI	0.33
Service (C3)			JE	EI	0.04
Risk (C4)				JE	0.15

Table 4. Local weights and pairwise comparison matrix of cost (C1) sub-criteria

Cost criteria	C11	C12	C13	C14	Weights
Product price (C11)	JE	SMI	VSMI	SMI	0.57
Maintenance cost (C12)		JE	EI		0.06
Freight cost (C13)			JE		0.06
Payment terms (C14)		WMI	SMI	JE	0.31

Table 5. Local weights and pairwise comparison matrix of quality (C2) sub-criteria

Quality criteria	C21	C22	C23	C24	Weights
Quality assurance (C21)	JE	SMI		SMI	0.39
Problem-solving capability (C22)		JE		WMI	0.14
Product quality (C23)	WMI	SMI	JE	SMI	0.45
Rejection rate (C24)				JE	0.02

Table 6. Local weights and pairwise comparison matrix of service (C3) sub-criteria

Service criteria	C31	C32	C33	C34	Weights
On-time delivery (C31)	JE	SMI	SMI	WMI	0.45
Technical support (C32)		JE	SMI		0.23
Response to changes (C33)			JE		0.02
Warranties (C34)		WMI	WMI	JE	0.30

Table 7. Local weights and pairwise comparison matrix of risk (C4) sub-criteria

Risk criteria	C41	C42	C43	C44	C45	Weights
Concept conflict (C41)	JE				EI	0.04
Geographical location (C42)	WMI	JE	WMI			0.16
Political stability (C43)	SMI		JE		EI	0.17
Financial stability (C44)	SMI	VSMI	SMI	JE	SMI	0.42
Foreign exchange rate (C45)		WMI			JE	0.21

In the following step, the degree of dependency among the criteria is determined by analysing the impact of each criterion on every other criterion using pairwise comparisons. In this way, pairwise comparison matrices are formed based on the dependencies represented in the second stage of Figure 3. The computed relative importance weights by their inner dependence matrices are given in Tables 8–11.

Table 8. Inner-dependency matrix of the criteria with respect to "cost"

Cost criteria	Quality criteria	Service criteria	Risk criteria	Weights
Quality criteria	JE	WMI		0.34
Service criteria		JE		0.1
Risk criteria	WMI	SMI	JE	0.56

Table 9. Inner-dependency matrix of the criteria with respect to "quality"

Quality criteria	Cost criteria	Service criteria	Risk criteria	Weights
Cost criteria	JE	WMI	VSMI	0.59
Service criteria		JE	EI	0.21
Risk criteria			JE	0.2

Table 10. Inner-dependency matrix of the criteria with respect to "service"

Service criteria	Cost criteria	Quality criteria	Risk criteria	Weights
Cost criteria	JE	WMI	WMI	0.45
Quality criteria		JE		0.15
Risk criteria		SMI	JE	0.41

Table 11. Inner-dependency matrix of the criteria with respect to "risk"

Risk criteria	Cost criteria	Quality criteria	Service criteria	Weights
Cost criteria	JE	SMI	VSMI	0.76
Quality criteria		JE	EI	0.08
Service criteria			JE	0.15

By multiplying the weights acquired from the inner-dependency matrices of the criteria (Table 8–11) with the local weights of the criteria (Table 3), the interdependent weights of the criteria are obtained. The normalized weights of the criteria were found as cost: 0.40, quality: 0.26, service: 0.09, and risk: 0.25. By multiplying the weights of the main criteria with the local weights of the sub-criteria, the global weights of the sub-criteria are obtained (Table 12).

Table 12. Global weights of criteria and sub-criteria

Criteria	Weights	Sub-criteria	Weights
Cost criteria (C1)	0.40	Product price (C11)	0.230
		Maintenance cost (C12)	0.025
		Freight cost (C13)	0.023
		Payment terms (C14)	0.126
Quality criteria (C2)	0.26	Quality assurance (C21)	0.099
		Problem-solving capability (C22)	0.037
		Product quality (C23)	0.117
		Rejection rate (C24)	0.004
Service criteria (C3)	0.09	On-time delivery (C31)	0.040
		Technical support (C32)	0.021
		Response to changes (C33)	0.002
		Warranties (C34)	0.027
Risk criteria (C4)	0.25	Concept conflict (C41)	0.009
		Geographical location (C42)	0.040
		Political stability (C43)	0.043
		Financial stability (C44)	0.105
		Foreign exchange rate (C45)	0.051

According to the results, the most important criterion in the determination of wind turbine supplier is cost, followed by quality and risk. The least weight is at the service criteria. While the two sub-criteria with the maximum weight in cost criterion are "production price" and "payment terms", the criteria with the least weights are "maintenance" and "freight costs". The most important determinant for quality was found to be "product quality"; for risk, "financial stability" and service, this determinant was "on-time delivery".

2.2. Formulation of f-MIGP for turbine supplier selection in wind power plant projects

In the second stage of the FANP-f-MIGP integrated model, the suppliers for each of the 3 different projects of the company are determined. The turbine types used in the projects are 3 MW (megawatt) for the first project, 2.3 MW for the second project, and

3.2 MW for the third project. The suppliers for the projects are selected among 3 firms that provide turbines for the company. In formulating the problem, a single supplier will be worked with in each project, thus requiring integer programming. Therefore, in determining the optimal suppliers for the projects, under certain constraints, an f-MIGP model is established that aims to realize all four objectives.

The decision variables of wind turbine supplier selection model are assigned as 0-1 integer, as stated below.

$$\text{Decision variable} = x_{ij} = \begin{cases} 1, & \text{if supplier } i \text{ is allocated to project } j \\ 0, & \text{otherwise} \end{cases},$$

where, i = supplier index, i = 1, 2, 3; j = project index, j = 1, 2, 3.

The objectives of the selection process are to minimize cost and risk and maximize quality and service. The coefficients of the objective function are established with the criteria weights obtained in the first stage with the FANP model.

The lower and upper bound of the goals for the selection model are summarized in Table 13. These bounds indicate the objective limits that the company sets for projects. The minimum and maximum goals are determined for each of the three projects by the decision-making team.

The cost, quality, service and risk factors related to each candidate supplier, S1, S2 and S3, are presented in Table 14.

Table 13. Goals for supplier selection

Criteria & constraints	Goals		Lower bound	Upper bound
G1	Minimize	Cost	7 750 000	8 850 000
G2	Maximize	Quality	144	156
G3	Maximize	Service	156	194
G4	Minimize	Risk	78	108

Table 14. Data set for suppliers with regards to the criteria

Supplier	Cost (€)	Quality (%)	Service (%)	Risk (%)
S1 for Project1	3 100 000	50	60	20
S1 for Project 2	2 800 000	50	60	30
S1 for Project 3	3 250 000	50	60	20
S2 for Project 1	2 750 000	55	50	30
S2 for Project 2	2 500 000	55	50	40
S2 for Project 3	3 000 000	55	50	40
S3 for Project 1	2 500 000	45	70	40
S3 for Project 2	2 250 000	45	70	20
S3 for Project 3	2 850 000	45	70	40

The company considers six constraints while selecting suppliers and it will only work with one of the three suppliers in each project. The first three constraints state this condition separately for these three projects. Besides, the company intends to allocate a maximum of two projects to each supplier in order to minimize the risk of possible future conflicts and procurement problems. This condition is defined with the last three constraints.

All the data mentioned above is used to apply the membership functions, and the final weights are calculated accordingly. The f-MIGP structure of the wind turbine supplier selection problem is formulated as follows:

$$\text{Max } 0.40\lambda_1 + 0.26\lambda_2 + 0.09\lambda_3 + 0.25\lambda_4,$$

$$\lambda_1 \leq \frac{8850000 - (3100000x_{11} + 2800000x_{12} + 3250000x_{13} + 2750000x_{21} + 2500000x_{22} + 3000000x_{23} + 2500000x_{31} + 2250000x_{32} + 2850000x_{33})}{1100000};$$

$$\lambda_2 \leq \frac{(50x_{11} + 50x_{12} + 50x_{13} + 55x_{21} + 55x_{22} + 55x_{23} + 45x_{31} + 45x_{32} + 45x_{33}) - 144}{12};$$

$$\lambda_3 \leq \frac{(60x_{11} + 60x_{12} + 60x_{13} + 50x_{21} + 50x_{22} + 50x_{23} + 70x_{31} + 70x_{32} + 70x_{33}) - 156}{38};$$

$$\lambda_4 \leq \frac{108 - (20x_{11} + 30x_{12} + 20x_{13} + 30x_{21} + 40x_{22} + 40x_{23} + 40x_{31} + 20x_{32} + 40x_{33})}{30};$$

$$x_{11} + x_{21} + x_{31} = 1;$$
$$x_{12} + x_{22} + x_{32} = 1;$$
$$x_{13} + x_{23} + x_{33} = 1;$$
$$x_{11} + x_{12} + x_{13} \leq 2;$$
$$x_{21} + x_{22} + x_{23} \leq 2;$$
$$x_{31} + x_{32} + x_{33} \leq 2,$$
$$\lambda_{j=1,2,3,4} \in [0,1], x_{ij} = 0 \text{ or } 1.$$

The optimal solution for this formulation is $x_{11} = 0$; $x_{12} = 0$; $x_{13} = 0$; $x_{21} = 1$; $x_{22} = 0$; $x_{23} = 1$; $x_{31} = 0$; $x_{32} = 1$; $x_{33} = 0$; $\lambda_1 = 0.77$; $\lambda_2 = 0.92$; $\lambda_3 = 0.37$ and $\lambda_4 = 0.60$. According to this result, the company selected supplier 2 for projects 1 and 3, and supplier 3 for project 2. In other words, the second supplier was assigned to two projects at once, the third supplier was assigned to only one project, and the first supplier was *not* appointed to any project at all. According to the success results obtained from the four factors, the highest rate belonged to the "quality" factor with 92% and the lowest one to "service" with 37%. In the optimal solution, the other goals (cost and risk) attained 77% and 60% success rates, respectively. With the suppliers it assigned to its projects, the company managed to succeed at most in terms of "quality"; however, with these suppliers, the success in terms of "service" was low. The objective function value is 0.73 as obtained through multiplying the factor success percentages by the factor weights. These values, together with other details, can be viewed in Table 15. In the optimal solution, the degree of achievement of the fuzzy goals ($\lambda_{max} = 0.73$) is significantly high.

In this case, the company appears to have achieved 73% of the goals it has set. The individual contributions of the goals to this achievement are 0.31, 0.24, 0.03 and 0.15, respectively. While the success rate of the company is high, in order to further this rate, the values pertaining to the cost and risk criteria, which have high objective function coefficients, need to be improved. For this purpose, the 92% success rate in quality, which is another factor with a high coefficient, has to also be achieved in these criteria. Overall, the company may opt for new suppliers or, alternatively, it may demand the present selected suppliers to focus more on the cost and risk values.

Table 15. Result of sensitivity analysis

Sensitivity analysis for the objective function coefficients					
Criteria	Solution value	Unit profit	Total contribution	Allowable min c(j)	Allowable max c(j)
λ_1: cost	0.77	0.40	0.31	0.36	0.69
λ_2: quality	0.92	0.26	0.24	0.24	0.49
λ_3: service	0.37	0.09	0.03	0	0.12
λ_4: risk	0.60	0.25	0.15	0.10	0.26

Objective function (max.): 0.73

Sensitivity analysis for the constraint functions					
Constraint	Direction	RHS*	Shadow price	Allowable min RHS	Allowable max RHS
C1	$\leq$	8850000	0	–M	M
C2	$\geq$	144	–0.0217	–M	155
C3	$\geq$	156	–0.0024	–M	170
C4	$\leq$	108	0.0083	90	M

Note: *RHS: right hand-side.

The results of the sensitivity analysis for the model are presented in Table 15, the first section of which presents the sensitivity analysis results for the objective function, and the second section presents the sensitivity analysis results of the constraint equations. The allowable minimum and maximum values in the table indicate the limits that the coefficients can reach without altering the current solution structure. These values allow the company to analyze how much of a variation in the coefficients of the four goals will change the optimal solution structure. Accordingly, with all other parameters remaining constant, the optimal result will not change even if the coefficient of the cost factor of 0.40 decreases to 0.36 or increases to 0.69. Similarly, this interval is between 0.24 and 0.49 for quality, 0 and 0.12 for service, and 0.10 and 0.26 for risk. Even if the company modifies the weights for these criteria within these intervals, the optimal solution structure will not change.

In the second section of Table 15, the sensitivity analyses are shown for the constraints that the company has determined concerning the cost, quality, service and risk fac-

tors. In this section, where the variations in the right-hand side (RHS) constants of the constraints are examined, the minimum/maximum RHS values and shadow prices are presented for each constraint equation. Accordingly, even if the company decreases its limit for the risk target of 108 all the way to 90, the solution structure will not change. However, if it decreases below this limit, another solution composition will emerge. Within these bounds, each time when the company increases the RHS value for the constraint related to the risk factor by one unit – in other words, when it expands the limit – the company's achievement percentage will increase by 0.083 units. On the other hand, when willing to decrease the risk if it tightens the limit, the success percentage will decrease proportionally. The maximum allowed limit values for the quality and service are 155 and 177, respectively. Restricting the limits of these constraints without exceeding them by, for instance, making compromises in the criteria will increase the percentages of the target achievements. Each unit of decrease in the RHS values of the quality and service constraints will, in turn, make for 0.02 and 0.0024 increase in success, respectively. On the other hand, changing the value of the cost constraint, which has a zero shadow price, has no binding effect on the overall success. Obviously, the acceptable limit values are also infinite. The company's increasing or decreasing the cost constraint will not change the total achievement percentage. Within the allowable minimum and maximum limits given earlier, the company may increase the target achievement level by the previously stated rates upon expanding the quality, risk and service constraints. By reviewing its pre-determined lower and upper bounds from this perspective, the company should evaluate whether any alterations need to be made, and assess whether the increase in the success percentage that these compromises will allow are worth the effort.

Conclusions

Regardless of the sector they operate in, selecting the accurate suppliers and establishing cooperation that provides competitive advantage is very important for companies. Until now, supplier selection has generally been conducted only for mass production systems, and the order quantities are determined by proposed integrated models. Yet, because in the supplier selection process for wind power plants that produce in a project-type manner, there is a necessity to work with a single supplier for each project, it is not naturally possible to divide the order quantity among different suppliers. Also, considering the fact that energy companies under take simultaneous and consecutive projects with high budgets and long life spans, it is vital to determine the optimal supplier with which they can establish long lasting relationships in order to realize the construction and post-construction processes without delay and with the desired quality.

In this study, an integrated FANP-f-MIGP model is suggested and applied to an energy company in order to select the optimal wind turbine supplier for each wind power plant project. With the suggested FANP-f-MIGP model, selection of turbine supplier is performed by considering both qualitative and quantitative factors. In the first stage of the model, by establishing the criteria specific to the selection of wind turbine suppliers, a network model that takes these criteria as the basis is developed and, later, solved using

the FANP method. In conclusion, the criterion which the company prioritises is cost, followed by risk and service. The weights of the four main criteria obtained constitute the coefficients of the objective function of f-MIGP model in the next stage. Under the defined constraints, the optimal supplier is selected considering cost and risk minimization as well as quality and service maximization. Accordingly, for projects 1 and 3, the second supplier, and for project 2, the third supplier has been selected by the company, whereas the first supplier has not been selected for any project at all. The company's target achievement percentage has been 73%, which is significantly high. Nevertheless, if it wishes to increase this ratio, it would be appropriate for the company to improve its efficiency concerning the cost and risk criteria, which have high objective function coefficients. In general, the company may opt for new suppliers with better performance, or demand improved operations from its current suppliers regarding these criteria. Another way for the company to increase its success rate is to expand the constraints it places on these targets. According to the findings, the cost constraint has no binding effect on the total success rate, although expanding the quality, risk and service constraints increases the success ratio up to a certain level. This allows the company to increase its success level by evaluating the pre-determined lower and upper limits for these constraints.

In the first stage of the suggested model, FANP is used, thereby providing the interaction and feedback both within and between the factors. Identification of the imprecise aspiration level for more than one objective is achieved via f-MIGP. With the FANP-f-MIGP integrated model, a decision mechanism is defined where the linguistic priorities of the decision-makers is considered indispensable for use under uncertain circumstances. The suggested model provides the chance to select the efficient supplier for wind power plant projects and other projects with similar characteristics.

For future studies, it is suggested that applications be increased through development of new criteria and models for other fields within the energy sector. Additionally, new options and settings may be established for different success rates, and the upper and lower target limits and supplier qualities required for the company to achieve these values may be re-defined. In this way, a company can re-determine the alterations it will need to make in terms of constraints, or alternatively seek new suppliers to achieve such success rates.

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