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Evaluation of Combined Heat and Power (CHP) Systems Using Fuzzy Shannon Entropy and Fuzzy TOPSIS

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Abstract: Combined heat and power (CHP) or cogeneration can play a strategic role in addressing environmental issues and climate change. CHP systems require less fuel than separate heat and power systems in order to produce the same amount of energy saving primary energy, improving the security of the supply. Because less fuel is combusted, greenhouse gas emissions and other air pollutants are reduced. If we are to consider the CHP system as "sustainable", we must include in its assessment not only energetic performance but also environmental and economic aspects, presenting a multicriteria issue. The purpose of the paper is to apply a fuzzy multicriteria methodology to the assessment of five CHP commercial technologies. Specifically, the combination of the fuzzy Shannon's entropy and the fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) approach will be tested for this purpose. Shannon's entropy concept, using interval data such as the α-cut, is a particularly suitable technique for assigning weights to criteria—it does not require a decision-making (DM) to assign a weight to the criteria. To rank the proposed alternatives, a fuzzy TOPSIS method has been applied. It is based on the principle that the chosen alternative should be as close as possible to the positive ideal solution and be as far as possible from the negative ideal solution. The proposed approach provides a useful technical–scientific decision-making tool that can effectively support, in a consistent and transparent way, the assessment of various CHP technologies from a sustainable point of view.

Keywords: combined heat and power (CHP); sustainability; fuzzy multicriteria; Shannon entropy; fuzzy TOPSIS

1. Introduction

In facing the very real threat of climate change, the European Commission has set a strategic target for its energy policy: to reduce greenhouse gas emissions by 2020 by at least 20% compared with the 1990 levels, in a way that is compatible with competitiveness objectives. To promote safety and sustainability, the European energy system must take action on four main fronts [1]:

- the conversion and efficient use of energy in all the sectors of the economy associated with a decline in energy intensity;
- the diversification of the energy mix towards renewable energy sources and technologies for energy conversion with low carbon emissions for electricity, heating and cooling;

- the decarbonization of transportation by shifting to alternative fuels;
- the complete liberalization and interconnection of energy systems using smart information and communication technologies to provide a flexible and interactive (customers/operators) service network.

Technology will play a strategic role in achieving the goals of the new energy policy for Europe. In 2007, under the European energy policy framework, the Commission intended to devise the first European strategic plan for energy technologies with the underlying objective of speeding up innovation in the energy technology field and thus motivating European industry to transform the risks arising from climate change and the assurance of new opportunities to increase competitiveness. In this context, combined heat and power (CHP) or cogeneration can play a strategic role in attempts to respond to environmental issues and climate change. Cogeneration is a technique that allows the production of both heat and electricity. As opposed to conventional power plants, in which exhaust gases are released by a chimney, the gases produced by cogeneration before being released in the atmosphere deliver their energy into a hot water or steam loop. Natural gas is the most commonly used fuel in CHP but, in many cases, renewable energy sources can also be employed. CHP saves energy and improves the security of the supply.

The EU Commission released the Directive 2004/8/EC of the European Parliament and of the Council of 11 February 2004 on the promotion of cogeneration, establishing a context to encourage and promote the installation of cogeneration plants [2]. The Directive should improve the context for high-efficiency CHP favouring the reduction of the greenhouse gas (GHG) emissions and other pollutants and contributing to sustainable development.

To imagine an energy scenario in which CHP can have a strategic role in sustainable development, it is a precondition to carry out a feasibility evaluation. The classical evaluation or optimization approaches are based on a single objective analysis of energetic or economic performance [3–5]. Other recent papers of interest that deal with modelling of CHP are as follows: Kupecki (2015) offers a paper about stationary off-design modelling of a micro-combined heat and power unit with fuel cells [6], Seijo *et al.*, (2016) propose a multi-objective optimization of a CHP plant [7], Wang *et al.*, (2015) developed a modeling and optimization method for planning and operating CHP based district heating systems with renewable energy production and energy storage [8], Rossi *et al.*, (2014) propose an effective modeling technique for determining baseline energy consumption of CHP plants [9], Kortela *et al.*, (2015) present a model predictive control (MPC) of the BioPower combined heat and power (CHP) plant [10], and Sanaye and Nasab, (2012) propose to optimize a CHP system introducing a defined objective function and specific design parameters [11].

Obviously, if we are to consider the CHP system as "sustainable", we must include in the assessment not only energetic performance but also environmental and economic aspects (3E). Then, this kind of problem certainly amounts to a multicriteria one. Multi Criteria Decision Analysis (MCDA) is attractive because it can handle large amounts of, often conflicting, information, data, relations and objectives that are generally encountered when conducting a specific comparison or assessment of different alternatives [12]. In MCDA, the decision-making process normally consists of making a choice between different elements examined by the decision maker and evaluating them using a set of criteria [13]. The core of MCDA contains the notion that all data, consequences and a prospects that a certain behaviour or action will meet and fulfil the set criteria are made available systematically and accurately. MCDA supports the decision-makers in structuring the problem and finding a justified and *not optimum* alternative [14]. For further methodological details on MCDA, see the extensive available literature.

In the literature, few contributions deal with CHP in multicriteria terms. In particular, we can mention the following: Wang *et al.*, (2008) who offered a fuzzy multicriteria decision-making model (FMCDM) for the selection and evaluation of several kinds of trigeneration systems [15]; Nieto-Morote *et al.*, (2011), who presented the case of the selection of a trigeneration system for a typical residential building [16]; Pilavachi *et al.*, (2006), who evaluated 16 kinds of CHP systems using a multicriteria method [17]; Wang *et al.*, (2009), who evaluated 16 kinds of CHP systems using weighting methodologies following a multicriteria approach [18]; Ebrahimi and Keshavarz (2013), who proposed a multicriteria sizing function (MCSF) for designing the optimum size and operating strategy of a residential micro-combined cooling heating and power (CCHP) system [19], and, finally, Carvalho, Lozano and Serra (2012), who proposed a mixed-integer linear programming (MILP) model to assess a trigeneration system to be installed in a hospital [20].

In many cases, the data set used in the assessment procedure is conditioned by uncertainty. Fuzzy sets seem an appropriate tool for approximate reasoning and allow decision-making with incomplete or uncertain information. Instead, some authors have used other approaches to handle uncertainties in MCDA. For example, Hyde *et al.*, (2003) proposed a Monte-Carlo simulation to define the uncertainty of input values of a renewable energy case study based on the PROMETHEE method [21], Troldborg *et al.*, (2014) defined a probability distribution using Monte-Carlo simulation for each of the criteria values [22] and Wang *et al.*, (2015) used the stochastic multicriteria acceptability analysis (SMAA) to assess CHP units [23].

In this paper, a fuzzy multicriteria assessment of five CHP commercial technologies will be proposed. Specifically, a combination of the fuzzy Shannon's entropy and fuzzy TOPSIS approaches will be tested for this purpose. The paper is then structured as follows: the next section presents a brief introduction of the basic concepts of fuzzy sets theory and fuzzy arithmetic operations. Section 3 describes the idea of entropy and the TOPSIS method, while in Section 4 the application of the proposed approach to the assessment of the CHP technologies is presented. Finally, Section 5 closes the paper with a conclusion.

2. Fuzzy Set Theory: Preliminaries

Fuzzy-set theory introduced by Lofti Zadeh (1965) [24] is based on the simple idea of introducing the degree to which an item belongs to some sets. The innovative contributions offered by fuzzy logic relate to the description of vague, imprecise and uncertain information. The introduction of fuzzy logic therefore considerably modifies all the underlying principles of traditional logic.

In the classical set theory, the membership rule that characterizes the elements of a set A of U can be fixed by the concept of membership function $\mu_A(x)$ which determines the relationship between the elements x and the set A taking only two values, 1 and 0 [25]. The set A is represented by a function $\mu_A : X \rightarrow \{0,1\}$:

$$\mu_A(x) = \left\{ \begin{array}{l} 1 \text{ if } x \in A \\ 0 \text{ if } x \notin A \end{array} \right\} \tag{1}$$

To describe gradual transitions, Zadeh (1965) introduced grades between 0 and 1 and the concept of graded membership [24]. The theory acknowledges that the concept of membership is not any more certain (either 1 or 0), but becomes fuzzy in the sense of representing partial belonging or degree of membership [26]. For an element in a universe that contains fuzzy sets, the transition between membership and non-membership can be gradual. This transition along various degrees of membership can be thought of as conforming to the fact that the boundaries of the fuzzy sets are vague and ambiguous [25].

If the level of membership for an element is equal to 1, it means that the element is unequivocally in that set, while if the membership is 0, the element is absolutely not in that set. Values between 0 and 1 are ambiguous cases. A fuzzy set is a set of items in which there are no clear-cut boundaries between the items that belong and the items that do not belong to it.

A fuzzy set can be described as a set of ordered pairs:

$$A = \{x, \mu_A(x)\}, \quad \forall x \in U \tag{2}$$

where $\mu_A(x)$ is the function that characterizes the fuzzy set, that is, the membership function that matches a real number in the interval [0,1] to each point of X and where the value of $\mu_A(x)$ represents the degree to which x belongs to A [24].

Therefore, a fuzzy set can be defined as a mapping or membership function of all possible points to the closed interval [0,1] where 0 and 1 represent respectively the lowest and the greatest degree of membership. Thus, for $0 < \mu_A(x) < 1$ x belongs to A only up to a certain degree so that a fuzzy set, although the vagueness of its boundaries, can be determined by relating a value between 0 and 1 to each element $x \in A$. Membership of an element from the universe in this set is measured by a function that attempts to describe vagueness and ambiguity [12].

If the universal set X is continuous, then the fuzzy set A can be represented as:

$$A = \int_x \mu_A(x)/x \tag{3}$$

Vice versa, if X is discrete, then A is:

$$A = \sum_i \mu_A(x_i)/x_i \tag{4}$$

The symbols Σ and ∫ indicate a union, while the symbol "/" does not represent a fraction, but the bond between a belonging value and the element to which it refers.

The support of a fuzzy set A in the universal set X is the crisp set that contains all the elements of X that have a degree of belonging to A that is not zero [25]. The support of a fuzzy set is obtained via the formula:

$$supp\ (A) = \{x \in X/\mu_A(x) > 0\} \tag{5}$$

The core of a fuzzy set A is the set of all points x in X such that $\mu A(x) = 1$. The core of a fuzzy set A is the set of all those elements of a universal set with membership grades of A that are equal to one and non-membership grades of A that are equal to zero [25].

$$Core\ (A) = \{x \in X/\mu_A(x) = 1\} \tag{6}$$

An important concept in fuzzy set theory is α-cuts. An α-cut of a fuzzy set A is a crisp set $A\alpha$, which contains all the elements of the universal set X that have a degree of membership of A greater than or equal to the value specified by α [27]. Let us suppose that we have a fuzzy set A made up of tall people and let us suppose that the measures of height that have a degree of membership of less than 0.95 are not of interest. It is thereby possible to create a fuzzy set in which the degree of membership of the respective x is greater than or equal to 0.95. This new fuzzy set, called A0.95, will be defined as follows:

$$A_\alpha = \{x \in X\,|\mu_A(x) \geqslant \alpha\} \quad a \in [0,\ 1] \tag{7}$$

The value 0.95 is called the "α-cut" and acts as a cut-off threshold since only it ensures that only the factors that have a degree of membership greater than or equal to the threshold value α (confidence level) will be taken into consideration. If the degree of membership equal to α is included, then the α-cut is termed a weak α-cut, and if the value is not included, then it is a strong α-cut.

Finally, a fuzzy set A is said to be convex if it satisfies the following conditions [26]:

$$\forall x, y \in X, \forall \lambda \in [0,1] \Rightarrow \mu_A(\lambda x + (1-\lambda)y) \geqslant \min(\mu_A(x), \mu_A(y)) \tag{8}$$

3. An Integrated Fuzzy Entropy and Fuzzy TOPSIS Approach

Over the last few decades, a number of studies have been carried out to identify useful practices and tools to aid policy makers in setting out energy strategies or technologies. In MCDA, the decision-making process consists usually in making a choice between different factors analyzed by the decision-makers. These methods analyze a decision problem by comparing a number of alternative actions on the basis of various evaluation criteria often in conflict with each other and allow rankings of the alternatives to be generated by assigning a score to each of them that is a measure of their utility. These methods are used not so much to identify the optimal solution but to generate the information needed for the decision to be made, highlighting amongst other things the conflicts between the different groups and individuals involved.

Multi-criteria methods provide a flexible tool that is able to handle and bring together a wide range of variables appraised in different ways and thus offer useful assistance to the decision maker in mapping out the problem [13,28].

In this section, we propose an integrated approach to perform a multicriteria assessment of combined heat and power system (CHP) options using a modified fuzzy TOPSIS. In particular, to find the vector weights, we use a modified version of Shannon's entropy adapted to deal with interval and fuzzy cases, proposed by Hosseinzadeh Lotfi and Fallahnejad (2010) [29], while for the ranking procedure, the fuzzy TOPSIS method is employed.

3.1. Shannon's Entropy for Objective Weighting

In a multicriteria approach, the weights attributed to the various criteria represent the importance of each criterion in the assessment procedure and directly produce effects on the ranking order of alternatives. Determining how to assign weights to the criteria remains one of the greatest weaknesses of this methodology. Indeed an arbitrary assignment of weights can greatly influence the result of the analysis [30]. In general, the analyst, to eliminate the uncertainty inherent in the attribution of the weights, can decide to give equal weights to all the criteria. This procedure requires very little knowledge on decisional priorities and can be used for many multicriteria decision tools. Dawes and Corrigan suggested that the equal-weighting method frequently produces results that are at least as good as precise numerical weights [31,32]. However, this method has been criticized because each criterion has different information and meanings and it is very hard to accept the idea that all the criteria can have the same weights [33]. As suggested by Jia Fischer & Dyer (1998) [32], several other authors have argued the superiority of the rank-order weighting method, which uses quantitative information concerning the relative importance of criteria [34–37].

In the literature, the methods for finding the weights are grouped into two classes: subjective and objective weights. The first class includes the methods that determine the weights exclusively according to the judgements of the decision makers. The subjective preference of DMs is based on their own knowledge and perception of the problem analyzed. Some mathematical tools, such as the eigenvector method Analytic Hierarchy Process (AHP), weighted least square method and Delphi method, are applied to calculate the overall decision-maker preference [38]. A review of various subjective weighting methods was provided by Hobbs (1980) [39] and Schoemaker & Waid (1982) [40]. The DM in some situations cannot always give consistent judgements and may obtain different weights from different weighting processes [41]. The difficulty of attributing reliable subjective weights is highlighted by some papers [42,43].

The objective methods, such as entropy and multiple objective programming, allow the vector weights to be obtained without any influence from the decision maker's judgements. In a few words, the objective weighting methods are based only on mathematical computation using the measurement data and information. The objective weighting approach is mostly applicable to situations in which credible subjective weights cannot be obtained or in cases in which the results of the MCDA process can be strongly influenced by the preference of the DM [41].

Among the objective weighting methods, the Shannon entropy concept [44] is a particularly useful approach for assigning weights to criteria. The entropy concept has an important role in information theory. It refers to a general measure of uncertainty in the data formulated in terms of probability [45] and it is used in the social sciences as well as in the physical sciences [46]. Kapur (1970) analyzes the connection between the concepts of entropy in information theory and physics and shows how Shannon's entropy leads to Boltzman distribution of statistical mechanics but fails to give the Fermi-Dirac and Bose Einstein distributions of quantum mechanics [47].

Therefore, entropy can be thought of as a measure of information content and it indicates how much can be learned from the data and how much is still unknown [48]. De Luca & Termini (1972) proposed a measurement of fuzziness that adapts the entropy concept [49], while other measures of fuzzy entropy have been proposed by Singpurwalla & Booker (2004) [50] and Emptoz (1981) [51]. Some authors have applied this concept to a wide range of topics, for example, Burg (1967) [52] in spectral analysis, Rosenfeld (1994) in language modelling [53] and Golan, Judge & Miller (1996) in economics [54]. Esmaeili *et al.* (2015) propose a fuzzy entropy method to identify the service quality attributes in a logistics company [55]. Kildiene *et al.* (2011) analyze the construction sector of the European countries using the multi-criteria COPRAS and entropy method to determine the weight of criteria [56]. Saparauskas, Zavadskas & Zenonas (2011) propose to compare different designs of building using entropy weight and utility theory [57]. Susinskas, Zavadskas & Turskis (2011) select the pile-columns alternatives applying the entropy method and Additive Ration Assessment (ARAS) method [58]. Son (2013) establishes a similarity measuring strategy of image patterns based on fuzzy entropy and energy variations [59]. Zhao and Guo (2014) propose a hybrid fuzzy multi-attribute decision-making approach (fuzzy entropy-TOPSIS) for selecting the best green supplier [60]. Won, Chung and Choi (2015) assessed the water use vulnerability using fuzzy TOPSIS coupled with the Shannon entropy method [61].

Finally, Erol *et al.* (2014) offer a multicriteria approach, based on fuzzy entropy and fuzzy compromise programming, to select a nuclear power plant site [62]. In Figure 1, the number of papers published from 2010 to 2014 searched for using the keywords "Energy" and "Fuzzy Entropy" and indexed by the Web of Science database (WoS) is shown.

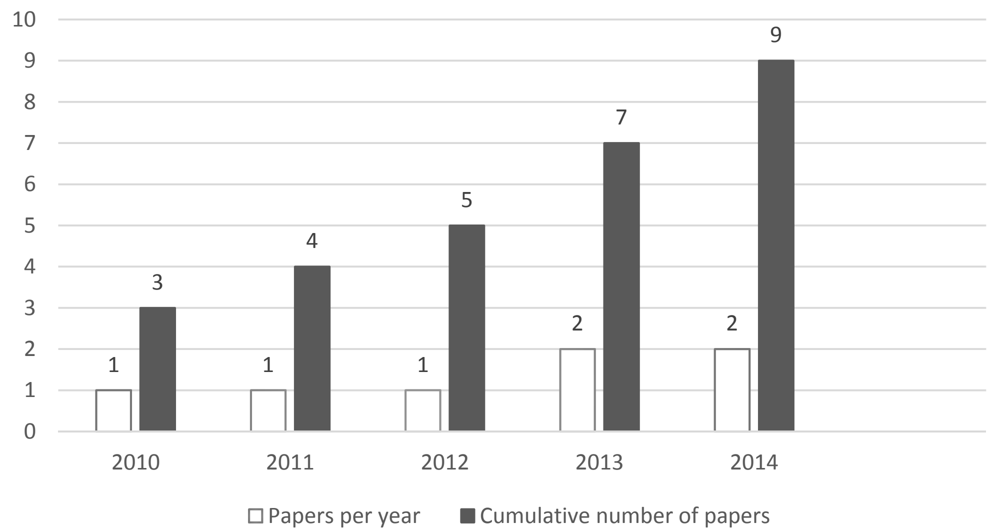

Figure 1. Papers (2010–2015) of fuzzy-entropy applications in the energy sector.

The entropy is particularly suitable for analyzing the contrast between data; it does not require a DM to rank the criteria and the vector weights can be obtained using a transparent computation procedure [63]. Fundamentally, entropy is a parameter that explains the grade of relative contrast intensity of the alternatives with respect to a specific aspect. A greater value of entropy corresponds to a smaller criterion weight. Thus, the less information the criterion provides, the less important and discriminate is the power that this aspect has in the decision-making process [45].

To calculate weights by the entropy measure, first of all the decision matrix has to be normalized by adjusting values measured on different scales to a notionally common scale.

Therefore, we have [44,45]:

$$p_{ij} = \frac{x_{ij}}{\sum_{i=j}^{m} x_{ij}},\ j = 1, \ldots, m \quad i = 1, \ldots n \tag{9}$$

After normalization, we can calculate the entropy values as:

$$e = -k \sum_{j=1}^{m} p_{ij} \ln p_{ij} \tag{10}$$

K is a constant equal to $(\ln m)^{-1}$, which assures $0 \leqslant e \leqslant 1$ and $p_{ij} \ln p_{ij} = 0$ if $p_{ij} = 0$. The larger the e, the less information is transmitted by the *jth* criterion. Then, the degree of divergence of the information of each criterion can be obtained:

$$d_j = 1 - e_j \tag{11}$$

The larger the d_j the more important the jth criterion is for the problem. Finally, the objective weight is obtained by the following equation:

$$w_j = \frac{d_j}{\sum_{s=1}^{n} d_s} \tag{12}$$

This expresses the degree of importance of the jth criterion.

3.2. Fuzzy Shannon's Entropy Based on Alpha-Cut

Hosseinzadeh Lofti and Fallahnejad (2010) propose an approach based on Shannon's entropy using interval data such as the α-cut [29]. Their method is based on the following procedure.

First of all, they propose to convert fuzzy data into interval data using alpha-level sets. The α-level set of a fuzzy variable can be illustrated in the following form:

$$\left[\left(\tilde{x}_{ij}\right)_{\alpha}^{L}, \left(\tilde{x}_{ij}\right)_{\alpha}^{R}, \right] = \left[\min_{x_{ij}} \left\{ x_{ij} \in R | \mu_{\tilde{x}_{ij}} \left(x_{ij}\right) \geqslant \alpha \right\}, \max_{x_{ij}} \left\{ x_{ij} \in R | \mu_{\tilde{x}_{ij}} \left(x_{ij}\right) \geqslant \alpha \right\} \right] \ 0 < \alpha \leqslant 1 \tag{13}$$

Then, the fuzzy data of the matrix will be transformed into α-cut interval data using Equation (13). By setting different levels of confidence of the α-cut, fuzzy data are transformed into different α-level sets.

$$\begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \left\{ \begin{array}{cccc} \left[x_{11}^{L}, x_{11}^{R}\right] & \left[x_{12}^{L}, x_{12}^{R}\right] & \cdots & \left[x_{1n}^{L}, x_{1n}^{R}\right] \\ \left[x_{21}^{L}, x_{21}^{R}\right] & \left[x_{22}^{L}, x_{22}^{R}\right] & \cdots & \left[x_{1n}^{L}, x_{1n}^{R}\right] \\ \vdots & \vdots & \vdots & \vdots \\ \left[x_{m1}^{L}, x_{m1}^{R}\right] & \left[x_{m2}^{L}, x_{m2}^{R}\right] & \cdots & \left[x_{mn}^{L}, x_{mn}^{R}\right] \end{array} \right\} \tag{14}$$

Thus, the values e_{ij}^{L} and e_{ij}^{R} are normalized:

$$p_{ij}^{L} = \frac{x_{ij}^{L}}{\sum_{j=1}^{m} x_{ij}^{R}},\ j = 1, \ldots m \quad i = 1, \ldots n \tag{15}$$

$$p_{ij}^{R} = \frac{x_{ij}^{R}}{\sum_{j=1}^{m} x_{ij}^{R}},\ j = 1, \ldots m \quad i = 1, \ldots n \tag{16}$$

Subsequently, the lower bound e_i^L and the upper bound e_i^R of the interval entropy can be calculated:

$$e_i^L = \min\left\{-e_0 \sum_{j=1}^{m} p_{ij}^L \cdot \ln p_{ij}^L,\ -e_0 \sum_{j=1}^{m} p_{ij}^R \cdot \ln p_{ij}^R,\right\},\ i = 1,\ldots n \quad (17)$$

$$e_i^R = \max\left\{-e_0 \sum_{j=1}^{m} p_{ij}^L \cdot \ln p_{ij}^L,\ -e_0 \sum_{j=1}^{m} p_{ij}^R \cdot \ln p_{ij}^R,\right\},\ i = 1,\ldots n \quad (18)$$

where $-e_0$ is equal to $(\ln m)^{-1}$ and $p_{ij}^L \cdot \ln p_{ij}^L$, or $p_{ij}^R \cdot \ln p_{ij}^R$ is equal to 0 if $p_{ij}^L = 0$ *or* $p_{ij}^R = 0$. To calculate the lower and upper bounds of the interval diversification d_{ij}^L and d_{ij}^R:

$$d_i^L = 1 - h_i^R,\ i = 1,\ldots,n \quad (19)$$

$$d_i^R = 1 - h_i^L,\ i = 1,\ldots,n \quad (20)$$

Finally, we obtain the lower and upper bounds of the interval weight of a criterion:

$$w_i^L = \frac{d_i^L}{\sum_{s=1}^{n} d_s^R} \quad (21)$$

$$w_i^R = \frac{d_i^R}{\sum_{s=1}^{n} d_s^L} \quad (22)$$

3.3. Fuzzy TOPSIS

The method for Order Performance by Similarity to Ideal Solution (TOPSIS) is one of the most important techniques for solving MCDM problems first developed by Hwang and Yoon (1981) [46]. It is based on the basic rule that the chosen alternative should be as far as possible from the negative ideal solution and as close as possible to the positive ideal solution. The negative ideal solution maximizes the cost criteria and minimizes the benefit criteria while the positive solution is the opposite, maximizing the benefit criteria and minimizing the cost criteria. The optimal performance is therefore the option that is farthest from the negative ideal solution and closest to the ideal solution.

The fuzzy TOPSIS method was selected from the various methods found in the literature because, firstly, it presents a transparent algorithm that can easily be understood; in addition, its efficacy and versatility have been widely tried and tested in many fields (economics, energy, environment, automation, industrial processes, robotics, management and many others); and, lastly, it is a flexible tool that can handle both quantitative and qualitative data well.

One of its main weaknesses, however, remains that of weighting; that is, assigning the degree of importance to the various criteria selected. Ascertaining weights is often subjective and may influence the final outcome.

A wide number of fuzzy TOPSIS methods have been developed in recent years. Wang and Chang (2007) suggested an application of TOPSIS to evaluate initial training aircraft [38]; Jahanshahloo *et al.*, (2006) extended the concept of TOPSIS to solve multicriteria problems with fuzzy data [64]; Liang (1999) produced a fuzzy multicriteria method based on the notions of ideal and anti-ideal points [65]; Li (1999) developed a very efficient fuzzy method to deal with multiple decisions made in a fuzzy environment [66]; Kahraman *et al.*, (2007) offered a fuzzy hierarchical TOPSIS model for industrial robotic systems [67]; Yong (2006) proposed a TOPSIS method for the selection of plant locations [68]; and Chen (2000) developed a version of the TOPSIS method for group decision making in a fuzzy context [69]. Yazdani-Chamzini *et al.*, (2013) propose a fuzzy hybrid model based on AHP, DEMATEL and TOPSIS techniques to select investment strategies [70]. Fouladgar, Yazdani-Chamzini & Zavadskas (2012) offer an approach to assess the risk of tunneling industry using fuzzy TOPSIS [71].

Furthermore, this method has been tested in many energy applications. In particular, the first article was published by Cavallaro (2010) that applied a fuzzy TOPSIS method to compare different heat transfer fluids (HTFs) for concentrated solar power [30]; Kaya & Kahraman (2011) proposed a modified fuzzy TOPSIS methodology for the selection of the best energy technology alternative [72]; Doukas *et al.* (2010) proposed an extension of TOPSIS to assess renewable energy source (RES) options using linguistic variables [73]; Chamodrakas & Martakos (2011) suggested the use of the fuzzy set representation TOPSIS for the selection of energy-efficient wireless networks [74]; Boran, Boran & Menlik (2012) applied intuitionistic fuzzy TOPSIS for the evaluation of renewable energy technologies for electricity generation in Turkey [75]; Yazdani-Chamzini *et al.*, (2013) assess renewable energy alternatives using an hybrid method based on COPRAS, TOPSIS and VIKOR [76].

Şengül *et al.*, (2015) employed a combined fuzzy TOPSIS and Shannon's entropy to rank renewable energy supply systems in Turkey [77] and Sianaki & Masoum (2013) used fuzzy TOPSIS for home energy management in a smart grid [78]. In Figure 2, the number of the published papers from 2010 to 2015 searching with the keywords "Energy" and "Fuzzy TOPSIS" and indexed by the Web of Science database (WoS) is shown.

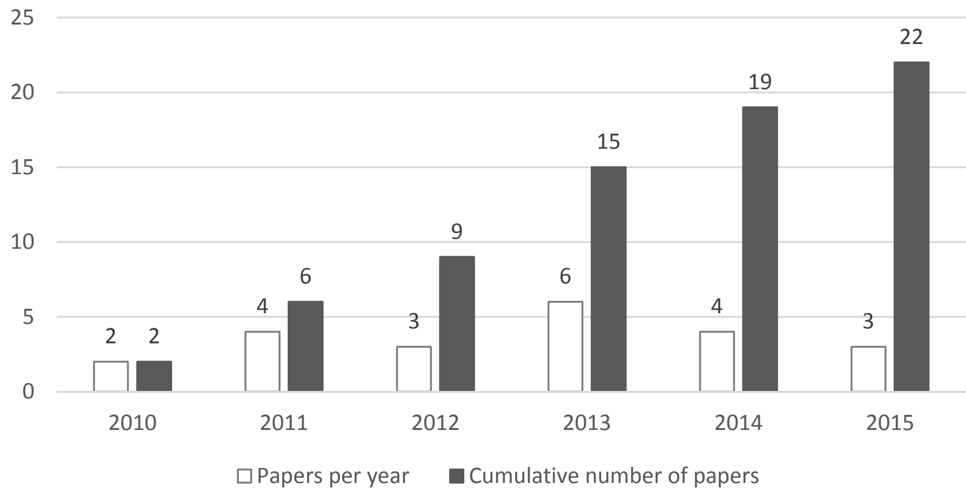

Figure 2. Papers (2010–2015) of fuzzy-TOPSIS applications in energy sector.

The procedure of the fuzzy TOPSIS is as follows: Suppose $A_1, A_2, \ldots, A_m$ are the m possible alternatives from among which decision makers have to choose, $C_1, C_2, \ldots, C_n$ denote the evaluation criteria used to measure the performance of the various alternatives and x_{ij} is the rating of the alternative A_i with respect to criterion C_j and it is a fuzzy number. A typical fuzzy multicriteria decision-making problem can be represented by a matrix format as follows:

$$\begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \left\{ \begin{array}{cccc} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{array} \right\} \quad i = 1, 2, \ldots, m; \quad j = 1, 2, \ldots, n \tag{23}$$

$$\tilde{W} = (\tilde{w}_1, \tilde{w}_2, \ldots, \tilde{w}_n) \tag{24}$$

where W_j is the weight of criterion C_j.

The approach to extend the TOPSIS method to fuzzy data can be described as follows [30,38,46,64,68]:

Step 1: identify alternatives;

Step 2: select the evaluation criteria;

Step 3: establish the weight of the criteria;

Step 4: build the fuzzy decision matrix;

Step 5: normalize the fuzzy decision matrix. The raw data are normalized using linear scale transformation to deliver the different criteria scales into a comparable scale.

Thus, the normalized fuzzy decision matrix will be as follows:

$$\widetilde{R} = \left[r_{ij}\right]_{mxn}, \quad i = 1,2,\cdots,m \quad j = 1,2,\ldots,n \tag{25}$$

$$r_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right), \quad j \in B \tag{26}$$

$$r_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right), \quad j \in C \tag{27}$$

$$c_j^* = \max_i c_{ij} \quad j \in B \tag{28}$$

$$a_j^- = \min_i a_{ij} \quad j \in C. \tag{29}$$

where B are the benefit criteria and C are the cost criteria. With the benefit and cost features, we can distinguish between the criteria that the decision-maker wishes to maximize and those that he/she desires to minimize, respectively.

Step 6: by considering the different weights of each criterion, we can build the weighted normalized fuzzy decision matrix as follows:

$$\widetilde{V} = \left[\widetilde{v}_{ij}\right]_{mxn} \quad i = 1,2,\ldots,m \quad j = 1,2,\ldots,n \tag{30}$$

$$\widetilde{v}_{ij} = \widetilde{r}_{ij} \otimes \widetilde{w}_{ij} \tag{31}$$

where W_{ij} represents the importance of criterion C_j.

Step 7: now we can calculate the fuzzy positive-ideal solution (FPIS, A^*) and fuzzy negative-ideal solution (FNIS, A^-) as follows:

$$A^* = (\widetilde{v}_1^*, \widetilde{v}_2^*, \ldots, \widetilde{v}_n^*) = \left\{\left(\max_i v_{ij} \,|j \in J\right), \left(\min_i v_{ij} \,|j \in J'\right)\right\} \tag{32}$$

$$A^- = \left(\widetilde{v}_1^-, \widetilde{v}_2^-, \ldots, \widetilde{v}_n^-\right) = \left\{\left(\min_i v_{ij} \,|j \in J\right), \left(\max_i v_{ij} \,|j \in J'\right)\right\} \tag{33}$$

$$\widetilde{v}_j^* = (1,1,1)\,;\ \widetilde{v}_j^- = (0,0,0)\,, \quad j = 1,2,\ldots,n. \tag{34}$$

Step 8: the distances between each alternative from A^* and A^- are determined using the following equations:

$$d_i{}^* = \sum_{j=1}^{n} d\left(\widetilde{v}_{ij}, \widetilde{v}_j{}^*\right), \quad i = 1,2,\ldots,m, \tag{35}$$

$$d_i{}^- = \sum_{j=1}^{n} d\left(\widetilde{v}_{ij}, \widetilde{v}_j{}^-\right), \quad i = 1,2,\ldots,m, \tag{36}$$

where d (.,.) is the distance measured between two fuzzy numbers.

Step 9: finally closeness coefficient (CC_i) of each alternative is computed. It is the distance to the fuzzy positive ideal solution A^* and the fuzzy negative ideal solution A^- simultaneously. Closeness coefficient determines the ranking order of all the alternatives as follows:

$$CC_i = \frac{d_i^-}{d_i^* + d_i^-}, \quad i = 1,2,\ldots,m \tag{37}$$

An alternative with a CC_i index close to 1 means that the alternative is close to the FPIS and far from the FNIS.

4. Development of an Application for Ranking Combined Heat and Power (CHP) Technologies

4.1. Combined Heat and Power (CHP) Technologies

As we said, combined heat and power (CHP) or cogeneration is a particular technology implemented to improve energy efficiency through the generation of heat and power in a single plant [79]. CHP is not a single technology, but an integrated energy system that can be adapted to the needs of the energy end user [80]. A fossil fuel power plant transforms about half of the primary energy content of its fuel into electricity and rejects the rest as "waste" heat [81].

In general, cogeneration is structured as a sequential generation of two forms of energy—mechanical and thermal—from a primary energy source. Mechanical energy can be used for producing electricity by a motor or turbine, while thermal energy can be employed for direct processes that need heat or indirectly for producing steam, hot water, hot air or chilled air for process cooling [82].

Cogeneration, or combined heat and power (CHP), recovers part of the heat to cover the heat demand otherwise produced by another fuel. In the conventional power plants, only about a third of the primary energy fed into system is really available in the form of electricity [83]. In addition, further losses of around 10%–15% derive from the transmission and distribution of electricity in the electrical grid. A significant economic advantage of the micro-scale CHP systems consists of the electricity production on-site so the transmission line losses are eliminated [83]. Commercial and macro-scale CHP plants instead are generally connected to heating and electric transmission lines.

CHP plants consist of four elements: the prime mover (heat engine or drive system), an electricity generator, a heat recoverer and electrical interconnections. The equipment that controls the electricity generator (prime mover) produces heat that can be recovered. Cogeneration units can run on a variety of fuels, although natural gas currently dominates the market. Natural gas offers numerous benefits, such as its high heating and low carbon content. It produces 40%–50% less CO2 than coal-fired CHP plants. Due to these characteristics, natural gas is the preferred fuel in the cogeneration systems. Other common fossil fuels (coal and diesel) are also used but especially municipal solid waste and biomass are becoming increasingly important. Another growing area of scientific and commercial interest focuses on the use of heat from geothermal sources.

Heat provided by CHP plants can be used for industrial process in any sector of economic activity or space-heating in the residential sector.

CHP technology works in an extensive range of energy-intensive industrial manufacturing industries, such as chemical, refining, pulp and paper. These industries represent more than 80% of the total CHP capacities [84]. These plants have a high heat demand for their processes that is not subject to seasonal and weather fluctuations. In recent years, the use of CHP has grown in commercial buildings (hotels, airports, campuses, office, buildings), multi-residential complexes (multi-family housing, planned communities), institutions (schools, universities and hospitals) and municipalities (district energy systems, wastewater treatment facilities,). CHP systems are very attractive for their economic, environment and energy benefits and because they produce energy where it is needed, avoiding waste heat and transmission and distribution losses. This means less fuel to produce a given energy output, less air pollution and greenhouse gas emissions and, last but not least, reduced energy-related costs.

CHP plants can use several kinds of prime mover technologies, with sizes ranging from 1 kWe to 500 MWe: fuel cells, steam turbines, gas turbines, microturbines, combined cycle systems, reciprocating engines or combustion turbines. Some of them are mature, reliable and proven technologies; others are less mature and more expensive but, in some cases, more efficient. Substantially, the technologies exhibit positive and negative aspects that can be evaluated with several conflicting criteria.

4.2. Algorithm and Results

Now we can now proceed to apply the methodology outlined in the previous sections using the following procedure (see the Figure 3):

Step 1: For this case study, first of all, we select some plants, in accordance with the catalogue of CHP technologies of the U.S. Environmental Protection Agency [85], consisting of:

(1) *Reciprocating engine*: it is a well-known technology used in cars, trucks, construction equipment, marine propulsion and backup power applications and it can range in size from small hand equipment to power systems serving many homes. Reciprocating engines employ the expansion of hot gases to push a piston within a cylinder, converting the linear movement of the piston into power. The high level of maturity and low-cost reliability make this option very interesting for CHP application.

(2) *Steam turbine*: this represents one of the most versatile and oldest prime mover technologies; in general, it is used to drive a generator or mechanical machinery. Steam turbines are well suited to medium- and large-scale industrial and institutional applications in which fuels, such as coal, biomass, various solid wastes and refinery residual oil, are available [86]. They can also be joined in a combined cycle using the waste heat from a gas turbine. In CHP applications, steam at lower pressure can be extracted from the turbine and used directly in industrial processes or for district heating or it can be employed to produce hot or chilled water [86]. For industrial applications, steam turbines are a simpler case of using CHP.

(3) *Gas turbine*: this is an aeroderivative technology; indeed, it began to be used in aeroplane propulsion in the 1940s. Since 1990, this technology has been employed for power only generation or in combined heat and power (CHP) systems in stationary applications in many countries of the world. In many cases, gas turbines are utilized by utilities to cover the energy demand peak. Gas turbines, available in sizes ranging from 150 kW to 250 MW, produce high-quality exhaust heat that can be used in CHP layout to reach overall efficiencies (electricity and thermal energy) of 70%–80% [87]. This makes gas turbines very attractive for CHP applications.

(4) *Microturbine*: this is an electricity generator that burns gaseous and liquid fuels that can be used in power-only generation or in CHP systems to produce both electricity and heat on a small scale. The microturbine technology was originally based on the truck turbocharger technology that exploits the energy in engine exhaust heat [88]. The size range is from 30 to 300 kW and they are able to operate with several fuels and, in (CHP) applications, they may take an increasing share of this market, offering more benefits compared with other technologies for small-scale power generation [89]. Microturbines are mechanically simple and very compact. Their small size and low weight per unit of power lead to reduced engineering costs, while the small number of moving parts produces less noise [90].

(5) *Fuel cells*: these are electrochemical systems capable of converting chemical energy of a fuel (generally hydrogen) directly into electricity without any direct combustion and intermediate thermal cycle. Since the fuel is not combusted, fuel cells offer a clean and efficient power generation system with very minimal air pollution. In CHP applications, the recovered heat depends on the type of fuel cell and its operating temperature. The parameters determining the performance of the fuel cell are dependent on the electrolyte material and composition of the membrane electrode assembly MEA [91]. The relationship of the materials to the performance of the device is significant and many important contributions in this topic can be found in the literature [92–97]. There are several kinds of fuel cells classified on the basis of the electrochemical process utilized. The principal types include: alkaline (AFC), polimer electrolyte (PEFC), phosphoric acid (PAFC), molten carbonate (MCFC) solid oxide (SOFC) and direct methanol (DMFC).

Step 2: Subsequently, the criteria are selected from the catalogue of CHP technologies of the U.S. Environmental Protection Agency [85]. In the context of multicriteria models, the criteria are the tools that allow alternatives to be compared from a specific viewpoint. The process of selecting criteria is very significant in framing the problem and, thus, it requires the greatest consideration to determine a coherent family of criteria. The number of criteria depends on the availability of the data-set. For this application, we selected the following: four technical criteria (C1, C2, C3 and C4) aimed to express several kinds of electrical and heat efficiency, two economic criteria (C5 and C6) about the investment and maintenance costs and, lastly, one environmental criteria (C7) concerning the GHG emissions reduction.

In particular, these are the selected criteria:

- (C1) Electric efficiency. This is defined as the ratio of the electric power output and the input power. In general it differs by technology and by size: larger systems are usually more efficient than smaller systems.
- (C2) Overall CHP efficiency. This expresses the energy content of both electricity and steam. It represents the net electrical power output plus the net thermal output (of the CHP system) divided by the fuel consumed.
- (C3) Fuel utilization. This measures the CHP efficiency as the ratio of net electrical output to net fuel consumption, in which the net fuel consumption does not include the share of fuel that produces the heat output.
- (C4) Power to heat ratio. This specifies the quantity of power (electrical or mechanical) to heat energy created in the CHP system.
- (C5) Installed costs. This criterion includes the costs of the equipment installation, project management, engineering and interest. Larger-capacity CHP systems in general have lower installed costs than smaller capacity systems.
- (C6) O&M costs. These include all the costs relating to the plant, employees' wages, materials and installations, preventive maintenance transport and hire charges. As with capital costs, also the O&M costs tend to be reduced for larger systems.
- (C7) GHG reduction. Because in CHP systems less fuel is combusted, greenhouse gas emissions such as carbon dioxide (CO2) and other air pollutants are decreased. This criterion expresses the avoided GHG emissions due to the CHP system.

Step 3: Now we can build the evaluation matrix (see Table 1), which contains the alternatives and the fuzzy data of the selected parameters.

Step 4: The assignment of the weights to the criteria surely represents the most important weakness of the multicriteria methodology. Nevertheless, some methodologies allow weights to be measured more objectively, such as Shannon's entropy based on the α -cut described earlier. Thus, we decide to use this approach to attribute the weights to criteria according to the following procedure:

Step 4.1: transform fuzzy data (Table 1) into interval data based on the alpha-cut using Equation (13);

Step 4.2: normalize the interval (alpha cut = 0.1, 0.5, 0.9) decision matrix according to Equations (15) and (16) (Table 2);

Step 4.3: calculate the lower bound and the upper bound of the interval entropy by Equations (17) and (18);

Step 4.4: compute the degree of diversification d_i^L and d_i^R using Equations (19) and (20);

Step 4.5: finally, by applying Equations (21) and (22), we obtain the lower and upper bounds of the interval weight, as shown in Table 3.

Step 5: The fuzzy matrix of Table 1 is normalized using Equations (26) and (27) to obtain homogeneous values on a single scale that is able to satisfy the membership function of triangular fuzzy numbers in the range [0,1].

Step 6: Afterwards, the weighted fuzzy matrix is calculated by multiplying the vector weights obtained by Shannon's entropy (Table 3) with the normalized fuzzy matrix.

Step 7: This step determines the FPIS, A^* and FNIS, A^- using Equations (32) and (33) and thereby calculates the distance of each option from A^* and A^- using Equations (35) and (36).

Step 8: Lastly, using Equation (37), we obtain the Cci (coefficient of closeness) and the ranking of the options is thus obtained and shown in Table 4 and Figure 4.

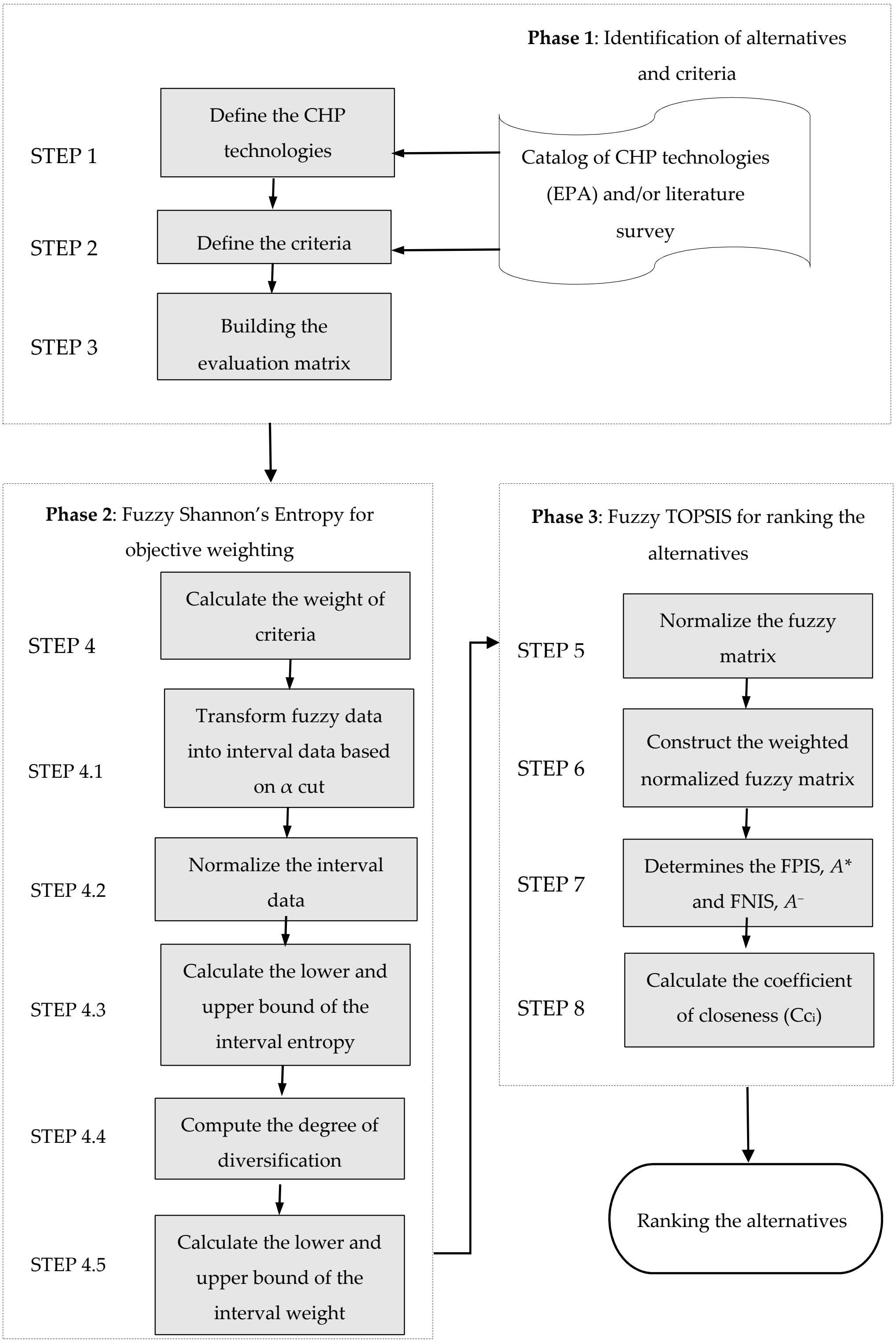

Figure 3. The proposed algorithm.

Table 1. Fuzzy evaluation matrix.

		C1	C2	C3	C4	C5	C6	C7
		Electric Efficiency (%)	**Overall CHP Efficiency (%)**	**Fuel Utilization (%)**	**Power to Heat Ratio (%)**	**Installed Costs ($/kWe)**	**O&M Costs ($/kWhe)**	**GHG Reduction (%)**
A1	Recip. engine	(27,34,41)	(77,78.5,80)	(75,77.5,80)	(0.5,0.85,1.2)	(1500,2200,2900)	(0.009,0.017,0.025)	(31.50,35,38.5)
A2	Steam turbine	(5,17.5,30)	(70,75,80)	(75,76,77)	(0.07,0.085,0.1)	(670,885,1100)	(0.006,0.008,0.01)	(38.70,43,47.3)
A3	Gas turbine	(24,30,36)	(66,68.5,71)	(50,56,62)	(0.6,0.85,1.1)	(1200,2250,3000)	(0.006,0.00095,0.13)	(41.40,46,50.6)
A4	Microturbine	(22,29,36)	(63,66.5,70)	(49,53,57)	(0.5,0.6,0.7)	(2500,3400,4300)	(0.009,0.011,0.13)	(47.70,53,58.3)
A5	Fuel cell	(30,46.5,63)	(55,67.5,80)	(55,67.5,80)	(1,1.5,2)	(5000,5750,6500)	(0.032,0.035,0.038)	(50.40,56,61.6)

Table 2. Normalized interval decision matrix (α-cut).

		C1	C2	C3	C4	C5	C6	C7
		Electric Efficiency (%)	**Overall CHP Efficiency (%)**	**Fuel Utilization (%)**	**Power to Heat Ratio (%)**	**Installed Costs ($/kWe)**	**O&M Costs ($/kWhe)**	**GHG reduction (%)**
				α = 0.1				
A1	Recip. engine	[0.143,0.208]	[0.204,0.211]	[0.213,0.226]	[0.107,0.234]	[0.090,0.162]	[0.101,0.249]	[0.125,0.150]
A2	Steam turbine	[0.032,0.149]	[0.186,0.210]	[0.213,0.218]	[0.014,0.020]	[0.040,0.062]	[0.064,0.101]	[0.154,0.185]
A3	Gas turbine	[0.127,0.183]	[0.175,0.187]	[0.143,0.174]	[0.126,0.216]	[0.074,0.167]	[0.065,0.130]	[0.165,0.197]
A4	Microturbine	[0.115,0.143]	[0.167,0.184]	[0.140,0.160]	[0.102,0.139]	[0.148,0.241]	[0.095,0.132]	[0.190,0.227]
A5	Fuel cell	[0.164,0.317]	[0.149,0.208]	[0.159,0.223]	[0.211,0.392]	[0.291,0.368]	[0.332,0.388]	[0.201,0.240]
				α = 0.5				
A1	Recip. engine	[0.174,0.214]	[0.211,0.215]	[0.222,0.230]	[0.150,0.228]	[0.115,0.159]	[0.145,0234]	[0.136,0.150]
A2	Steam turbine	[0.064,0.135]	[0.197,0.210]	[0.220,0.223]	[0.017,0.021]	[0.048,0.062]	[0.078,0.100]	[0.167,0.185]
A3	Gas turbine	[0.154,0.188]	[0.182,0.189]	[0.155,0.172]	[0.161,0.217]	[0.103,0.159]	[0.086,0.125]	[0.179,0.197]
A4	Microturbine	[0.134,0.151]	[0.176,0.185]	[0.149,0.160]	[0.122,0.145]	[0.184,0.240]	[0.111,0.134]	[0.206,0.227]
A5	Fuel cell	[0.218,0.312]	[0.166,0.200]	[0.179,0.215]	[0.278,0.390]	[0.335,0.381]	[0.373,0.407]	[0.217,0.240]
				α = 0.9				
A1	Recip. engine	[0.211,0.220]	[0.219,0.219]	[0.232,0.234]	[0.203,0.221]	[0.145,0.155]	[0.197,0.216]	[0.147,0.150]
A2	Steam turbine	[0.103,0.119]	[0.208,0.211]	[0.228,0.229]	[0.021,0.022]	[0.059,0.062]	[0.095,0.100]	[0.181,0.185]
A3	Gas turbine	[0.187,0.194]	[0.190,0.192]	[0.167,0.170]	[0.206,0.218]	[0.137,0.149]	[0.111,0.120]	[0.194,0.197]
A4	Microturbine	[0.157,0.161]	[0.185,0.186]	[0.158,0.161]	[0.147,0.152]	[0.225,0.238]	[0.131,0.136]	[0.223,0.227]
A5	Fuel cell	[0.285,0.306]	[0.185,0.192]	[0.199,0.207]	[0.362,0.387]	[0.387,0.397]	[0.421,0.429]	[0.236,0.240]

According to the results of the computation shown in Figure 4 and Table 4, the ranking is as follows: gas turbine (A3) > steam turbine (A2) > fuel cell (A5) > reciprocating engine (A1) > microturbine (A4). To test the robustness of the obtained ranking, three levels of α-cut were used for a sensitivity analysis. In this study, α = 0.1, α = 0.5 and α = 0.9 were performed and produced the same ranking. The best position in the final ranking, occupied by the gas turbine (A3), may be generally attributed to its high reliability, low emissions of air pollutants and high grade of heat available. The steam turbine (A2) is ranked second thanks to its high overall efficiency (steam to power) and relatively low investment cost. Besides, this technology has the important advantage that it can be mated to a boiler firing a large kind of gaseous liquid and solid fuels. Next, there are fuel cells (A5) that, although penalized by high cost, have a good efficiency over loads and a low grade of pollutant emissions. The recip. engine (A1) has as its advantages fast start-up and a good load following capability but unfortunately it is limited to lower temperature cogeneration applications. Finally, the bottom-ranked option is the microturbine (A4) unfortunately penalized by high costs.

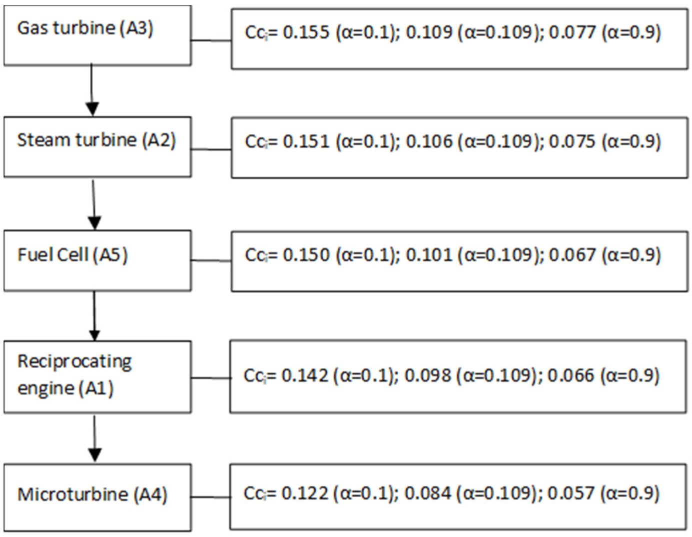

Figure 4. Ranking of alternatives.

Table 3. Interval and crisp vector weights.

	A = 0.1			A = 0.5			A = 0.9		
	w_i^L	w_i^R	w_i	w_i^L	w_i^R	w_i	w_i^L	w_i^R	w_i
C1	0.022	0.743	0.38	0.033	0.420	0.23	0.065	0.142	0.10
C2	0.001	0.152	0.08	0.001	0.082	0.04	0.003	0.018	0.01
C3	0.005	0.189	0.10	0.007	0.109	0.06	0.015	0.036	0.03
C4	0.106	0.876	0.49	0.155	0.607	0.38	0.275	0.383	0.33
C5	0.064	0.774	0.42	0.104	0.530	0.32	0.209	0.313	0.14
C6	0.063	0.783	0.42	0.104	0.537	0.32	0.213	0.320	0.27
C7	0.006	0.227	0.12	0.009	0.130	0.07	0.017	0.042	0.03

Table 4. Final ranking.

	A = 0.1				A = 0.5				A = 0.9			
	d^+	d^-	Cc_i	Rank	d^+	d^-	Cc_i	Rank	d^+	d^-	Cc_i	Rank
A1	6.043	1.001	0.142	4	6.345	0.686	0.098	4	6.558	0.467	0.066	4
A2	5.975	1.066	0.151	2	6.281	0.744	0.106	2	6.490	0.526	0.075	2
A3	5.950	1.095	0.155	1	6.267	0.764	0.109	1	6.484	0.541	0.077	1
A4	6.151	0.858	0.122	5	6.419	0.587	0.084	5	6.607	0.398	0.057	5
A5	5.987	1.053	0.150	3	6.312	0.712	0.101	3	6.546	0.470	0.067	3

5. Conclusions

Combined heat and power (CHP) technology or cogeneration surely represents a useful system to produce electricity and thermal energy from a single fuel source. It certainly can play a strategic role in improving energy efficiency and achieving sustainable objectives. CHP reduces the need for additional fuel combustion for the generation of heat reducing the emission of GHG and other air pollutants. Cogeneration is a form of distributed generation that can be utilized in many applications and can be placed near the energy consuming building. To evaluate the sustainability grade of CHP technologies, we need to include in the assessment process not only the energetic performance but also the environmental and economic aspects. For this purpose, a combination of the fuzzy Shannon's entropy and fuzzy TOPSIS approaches was applied. Shannon's entropy concept, using interval data such as the α-cut, is a particularly suitable technique for assigning weights to criteria. Furthermore, it does not require a DM to rank the criteria and the vector weights can be obtained using a transparent computation procedure. To rank the proposed alternatives, a fuzzy TOPSIS method was applied. It is based on the principle that the chosen alternative should be as close as possible to the positive ideal solution and as far away as possible from the negative ideal solution. According to the results, the obtained ranking is as follows: gas turbine (A3) > steam turbine (A2) > fuel cell (A5) > recip. engine (A1) > microturbine (A4). To test the robustness of the result, three levels of alpha-cut (0.1, 0.5, 09) were used for a sensitivity analysis that produced the same ranking. The best position in the final ranking, occupied by the gas turbine (A3), may be attributed to its general high reliability, low emissions of air pollutants and high grade of heat available. The steam turbine (A2) ranks second thanks to its high overall efficiency (steam to power) and relatively low investment cost. The fuel cell (A5) is positioned in the middle of the final ranking. Even if this technology is environmentally sustainable with a high energy conversion efficiency, this analysis it was found to have a high investment cost (criterion 5) and O & M cost (criterion 6) (see Table 1). Furthermore the Shannon-entropy method assigns to these criteria a high weight so as to influence the global performance ranking of fuel cells.

We obtain the ranking shown in Figure 4 on the basis of the used data (EPA-USA) and the criteria weights, if we use other data from different sources or if we apply a modified criteria vector, we may obtain different rankings. It means that MCDA in general does not provide an "optimum" solution but it supports the decision-making process in order to find (build) a suitable alternative.

It should be clear that the results obtained in this investigation are conditioned by the current performances of the selected CHP technologies. Surely, in the future, for some of the CHP plants analyzed here, technological progress will allow for improvements of many features of the CHP devices increasing efficiency and reliability. In particular, the development of new materials and improvements in manufacturing processes will play a key role in reducing investment costs and increasing competitiveness. It is important to highlight that the future development of these economic and productive factors can influence the results of this analysis and impact the rankings.

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