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Supportiveness of Low-Carbon Energy Technology Policy Using Fuzzy Multicriteria Decision-Making Methodologies

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Abstract: The deployment of low-carbon energy (LCE) technologies and management of installations represents an imperative to face climate change. LCE planning is an interminable process affected by a multitude of social, economic, environmental, and health factors. A major challenge for policy makers is to select a future clean energy strategy that maximizes sustainability. Thus, policy formulation and evaluation need to be addressed in an analytical manner including multidisciplinary knowledge emanating from diverse social stakeholders. In the current work, a comparative analysis of LCE planning is provided, evaluating different multicriteria decision-making (MCDM) methodologies. Initially, by applying strengths, weaknesses, opportunities, and threats (SWOT) analysis, the available energy alternative technologies are prioritized. A variety of stakeholders is surveyed for that reason. To deal with the ambiguity that occurred in their judgements, fuzzy goal programming (FGP) is used for the translation into fuzzy numbers. Then, the stochastic fuzzy analytic hierarchical process (SF-AHP) and fuzzy technique for order performance by similarity to ideal solution (F-TOPSIS) are applied to evaluate a repertoire of energy alternative forms including biofuel, solar, hydro, and wind power. The methodologies are estimated based on the same set of tangible and intangible criteria for the case study of Thessaly Region, Greece. The application of FGP ranked the four energy types in terms of feasibility and positioned solar-generated energy as first, with a membership function of 0.99. Among the criteria repertoire used by the stakeholders, the SF-AHP evaluated all the criteria categories separately and selected the most significant category representative. Finally, F-TOPSIS assessed these criteria ordering the energy forms, in terms of descending order of ideal solution, as follows: solar, biofuel, hydro, and wind.

Keywords: low-carbon energy (LCE); clean energy technology; policy; multicriteria decision making (MCDM); fuzzy methodologies; SWOT; FGP; SF-AHP; F-TOPSIS

1. Introduction

The use of energy is one of the most critical aspects in today's society, as it participates in all expressions of human development (industrial, economic, urban, and rural). For competent authorities, it is also of great importance to develop clean technologies, mechanisms, and policies that control regional resources and direct the regional development via the use of renewable and environment-friendly energy forms. Thus, energy conservation and sustainability are equally important in energy planning decision making. For that reason, the European Commission has suggested, consequently, from 2014 and every year, a guideline to create a sustainable energy action plan (SEAP) to include actions for the transition towards sustainable energy technologies. Via this European level action, the body of European Governors had agreed to reduce atmospheric CO_2 at least 20% by 2020, a goal which was never reached.

The key action for the modern regions is, therefore, to determine trajectories for establishing policies in order to advance the use of renewable low-carbon resources for clean power generation systems with techno-commercial viability, including solar, wind, hydro, and even hydrogen energy conversion and storage installations capacity and response for efficient utilization [1–4], while also minimizing the reliance on non-renewable fossil energy resources. Another primary goal is to promote initiatives that would lead to bioenergy development in biomass and waste biorefineries for increased production and use of sustainable biofuels [5–9]. Adopting an energy shift towards multifaceted low-carbon technologies with sustainable nature and related policies would be to positively contribute to slow down greenhouse gas cumulative emissions for addressing the climate change crucial problem [10–12].

At the same time, the following critical question arises: Is it feasible from an economical point of view to accomplish these energy transitions? Investors surely understand the environmental gain from such a shift to renewable energy usage, but certain reluctance still remains due to the lack of an optimal solution to this problem [13]. The aforementioned conditions and restrictions make the problem of energy planning and decision making a more complex one [14]. The conventional multicriteria decision-making (MCDM) methodologies are not convenient to deal with this problem, as a participatory modeling fuzzy environment is needed where all criteria in decision making, all uncertainties related to energy form selection, and all subjectivities would be expressed with linguistic variables instead of crisp-valued quantities [15,16]. The application of MCDM methods with participation of fuzzy variables is promising in dealing with the vagueness in the process and revealing the most influential factors associated with the embedded uncertainties in decision making.

Most of the studies that include fuzzy methodologies in the energy MCDM problem focus on the following: (a) evaluation of a certain type of energy resource [17], (b) determination of an energy policy for an energy usage alternative [18–20], and (c) power plant selection towards renewable energies [21–23].

The main objective of the present original research is to evaluate participatory modeling as a primary methodology for supporting a policy making process for the implementation of low-carbon energy technologies. Using this method, first, competent authorities design a multitude of scenarios based on regional environmental, economic, social, political, and health factors. The interoperability of these parameters is not always constructive, as there can be negative or inverse causalities between any two of these factors. In participatory modeling, regional stakeholders contribute to the buildup of these causalities. Their opinion is obtained either by surveys or focus groups. Thus, linguistic or intuitionistic variables are used for capturing this information. After all data are acquainted, fuzzy methodologies are employed for evaluating the various scenarios and also selecting a specific energy technology alternative. The application of participation modeling via surveys and focus groups succeeds to record stakeholder preferences as fuzzy numbers initially. Four different candidate energy types (solar, hydro, biofuel, and wind) are first evaluated by the fuzzy goal programming methodology in terms of their feasibility according to the criteria set by the stakeholders. This succeeds in transforming the problem from multiple objective into a single goal, i.e., to rank the energy types according to the primary criteria. For this reason, the stochastic fuzzy analytic hierarchical process (SF-AHP) is involved for evaluating the interrelations among the criteria and computing the pairwise fuzzy weight matrices. Later, the fuzzy technique for order performance by similarity to ideal solution (F-TOPSIS) methodologies is used to find near optimal solutions based on the predefined criteria that were used for the evaluation. The aim is to optimize the achievement of this decision-making process relative to the preset criteria, their pairwise relations, and the preset goals.

The structure of the paper is as follows: In the following section, we present all the material and methods related to SWOT (strengths, weaknesses, opportunities, and threats), FGP (fuzzy goal programming), SF-AHP, and F-TOPSIS methodologies, each one covering its own subsection. At the same time, we provide the necessary literature review in each subsection when we lay out each one and every methodology. In section three, we use a combined analysis for the SWOT and the SF-AHP to determine priorities of criteria or alternative policies in the decision matrix. The steps in this analysis are the same as in conventional AHP studies, i.e., (i) setting up the hierarchy, (ii) setting up the weight scale, and (iii) creating the decision matrix. The last is also created for the F-TOPSIS methodology with the use of triangular fuzzy numbers. In addition, FGP previously computed the importance of the criteria used in SF-AHP and F-TOPSIS method. Our results and discussion follow in the next section with the application of the methodology in Thessaly Region, Greece. In the final section, we discuss conclusions and future challenges for the issue.

2. Material and Methods

2.1. Strengths, Weaknesses, Opportunities, and Threats (SWOT) Analysis

Strengths, weaknesses, opportunities, and threats (SWOT) analysis (see Figure 1) is a planning methodology for project managers and decision makers to organize and highlight all above characteristics in a use case of decision making or a project. This analysis is at a preliminary stage, at the very first high level, and it is intended to mark all the objectives, as well as the internal and external factors that affect the process achieving these objectives. The interoperability and interrelationship between the internal and external factors are usually handled by means of the strategic fit of the decision making and affect later steps in this planning analysis to achieve the objective (such as AHP). The SWOT analysis is usually the first step applied in most of the energy planning methodologies [24,25]. Furthermore, the SWOT analysis is used to analyze stakeholder perceptions according to the decision-making process at hand [26], moving from a top-down to a bottom-up approach.

Figure 1. Cognitive map of the strengths, weaknesses, opportunities, and threats (SWOT) analysis.

2.2. Stochastic Fuzzy Set Theory and Fuzzy Analytic Hierarchal Process

Introduced by Zadeh [27], fuzzy sets are the means to present uncertainty due to imprecision or vagueness. Fuzzy sets are able to present data of linguistic variables and imprecise values. A fuzzy set is characterized by the notion of membership as a function which assigns a grade of membership to each entity in the set (a normalized value between 0 and 1). Fuzzy theory also includes the necessary mathematical operators and programming to apply to the fuzzy domain [28–32].

The AHP was introduced by Saaty [33] and has become the most popular method used for MCDM. However, AHP has shown some noticeable drawbacks because the variables involved in the method must be valued with exact crisp numbers. For that reason, fuzzy AHP (FAHP) was developed as an extension to AHP [34]. Special note here is given to the triangular fuzzy number which is defined by the triplet $(l,\ m,\ u)$ where $(l \le m \le u)$, (see Figure 2).

$$\mu(x) = \left\{ \begin{array}{ll} \frac{x-l}{m-l} & l \le x \le m \\ \frac{u-x}{u-m} & m \le x \le u \\ 0 & otherwise \end{array} \right\} \quad (1)$$

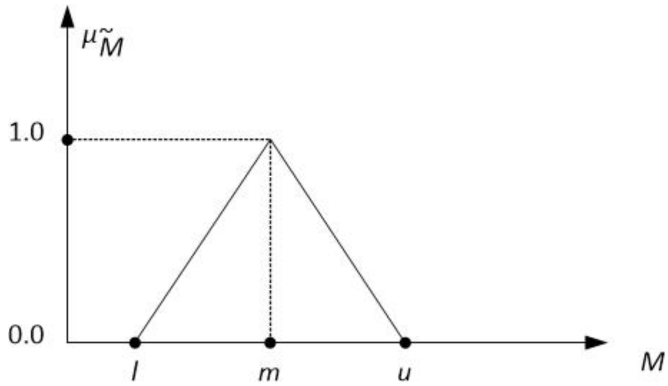

Figure 2. The presentation of a triangular fuzzy number.

Note that m indicates the mean and the most possible value, where l and u denote the smallest and the largest possible value, respectively.

According to the method, first, the experts recommend natural linguistic terms (e.g., equally important and weakly important) to express their judgments in fuzzy AHP and compare any two criteria pairs [35,36] (see Table 1). The pairwise comparison between any two criteria is based on a nine-integer scale shown where vales in between can be used. Table 1 presents the corresponding fuzzy value of this linguistic comparison.

Table 1. Equivalence between linguistic values and triangular fuzzy numbers.

Definition	Crisp Values (Intensity of Importance)	Fuzzy Triangular Scale $\widetilde{M}$=(l,m,u)
Equally important	1	(1,1,1)
Weakly important	3	(1,3,5)
Fairly important	5	(3,5,7)
Strongly important	7	(5,7,9)
Absolutely important	9	(7,9,9)

(Values 2,4,6,8 correspond to intermediate values to compromise between the previous ones).

According to the previous notation, it is worthwhile to present the most common algebraic operations between any two fuzzy numbers and a compact description of how the judgement matrix is calculated in the SF-AHP [37–40].

$$\widetilde{M} = (l, m, u) \quad (2)$$

$$(\widetilde{M})^{-1} = (l, m, u)^{-1} = \left(\frac{1}{u}, \frac{1}{m}, \frac{1}{l}\right) \quad (3)$$

$$\widetilde{M}_1 \oplus \widetilde{M}_2 = (l_1, m_1, u_1) \oplus (l_2, m_2, u_2) = (l_1 + l_2, m_1 + m_2, u_1 + u_2) \quad (4)$$

$$\widetilde{M}_1 - \widetilde{M}_2 = (l_1, m_1, u_1) - (l_2, m_2, u_2) = (l_1 - l_2, m_1 - m_2, u_1 - u_2) \quad (5)$$

$$\widetilde{M}_1 \otimes \widetilde{M}_2 = (l_1, m_1, u_1) \otimes (l_2, m_2, u_2) = (l_1 l_2, m_1 m_2, u_1 u_2) \quad (6)$$

Using the equations above for the addition and the multiplication of fuzzy numbers, we also show the formulas for the inner product and the summation of multiple fuzzy numbers needed for the calculation of the judgement matrix:

$$\prod_{i=1}^{n} \widetilde{M}_i = \left(\prod_{i=1}^{n} l, \prod_{i=1}^{n} m, \prod_{i=1}^{n} u \right) \tag{7}$$

$$\sum_{i=1}^{n} \widetilde{M}_i = \left(\sum_{i=1}^{n} l, \sum_{i=1}^{n} m, \sum_{i=1}^{n} u \right) \tag{8}$$

Using the answers (values) for the criteria under judgement for reaching the goal of the SF-AHP, the judgement matrix must be calculated according to the following equation:

$$\widetilde{M}_{ij} = \begin{bmatrix} \widetilde{M}_{11} & \widetilde{M}_{12} & \cdots & \widetilde{M}_{1n} \\ \widetilde{M}_{21} & \widetilde{M}_{22} & \cdots & \widetilde{M}_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ \widetilde{M}_{n1} & \widetilde{M}_{n2} & \cdots & \widetilde{M}_{nn} \end{bmatrix} = \begin{bmatrix} l_{11}m_{11}u_{11} & l_{12}m_{12}u_{12} & \cdots & l_{1n}m_{1n}u_{1n} \\ l_{21}m_{21}u_{21} & l_{22}m_{22}u_{22} & \cdots & l_{2n}m_{2n}u_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ l_{n1}m_{n1}u_{n1} & l_{n2}m_{n2}u_{n2} & \cdots & l_{nn}m_{nn}u_{nn} \end{bmatrix} \tag{9}$$

$$\text{for} \quad \begin{matrix} i = 1..n \\ j = 1..n \end{matrix}$$

For each one of the criteria under study we also have to calculate the geometric mean of the values of the matrix above, because it is needed to convert the fuzzy numbers back to crisp numbers and to normalize them. This is via the equation:

$$\widetilde{F}_i = \widetilde{R} \otimes \widetilde{G}_i = \left(\sum_{i=1}^{n} \sqrt[n]{\prod_{j=1}^{n} \widetilde{M}_{ij}} \right)^{-1} \otimes \sqrt[n]{\prod_{j=1}^{n} \widetilde{M}_{ij}}, \tag{10}$$

where $\widetilde{G}_i$ is the fuzzy geometric mean of the criterion C_i, R is the reciprocal of the sum of the geometric mean of fuzzy comparison values, and $\widetilde{F}_i$ represents the fuzzy weight for criterion C_i. The last step of the algorithm to compute the weights for each one of the criteria in this methodology is to find the normalized value of the mean of the fuzzy weights above so that for all criteria these weights must add up to 1. We must also add, for the case in which we have more than one expert that we contribute to the decision-making process, the previous methodology must be repeated each time.

In the last few years, the method has started to be widely used in the decision-making processes regarding supplier evaluations. There is a plethora of research works which have just been published also in relation to the subject at hand and for which we include, here. a synoptic reference:

In a recent work [41], the authors investigated supply chain sustainability by using the Pythagorean fuzzy analytic hierarchy process for the Indian manufacturing industry using the engagement of stakeholders. The study proved that the sustainable supply chain innovation along with social, environmental, and economic advancements were the key factors in improvement of the manufacturing industries. Towards the same line, other researchers [42] used the SF-AHP method to explore dilemmas regarding the solar energy in Taiwan buildings and analyzed the economic development of energy exploiting and environmental protection as the main categories of setting up criteria. Their findings indicated that the method used provided an operational evaluation decision-making system model. Furthermore, 15 representative energy enterprises in China were investigated and their performance was evaluated [43]. SF-AHP for F-TOPSIS was applied to rank the enterprises accordingly and they recommended differentiated subsidy policies for uncertainty evaluation to increase the credibility of the results. Since the problem at hand is of an international nature and it is a reality for most undergrown countries, another work [44] dealt with the evaluation of the renewable resource alternatives in Pakistan employing SWQIT analysis with SF-AHP to assess the internal and external factors which affect the renewable energy technologies. More specifically the SF-AHP was used as a multi-perspective approach to study the solar, wind, and biomass energy types identifying that economic and socio-political were the two most important criteria, thus suggesting that there must be a priority of the government to exploit renewable resources to mitigate the current energy crisis. In addition, other researchers agreed with the aforementioned conclusion when they dealt with similar problems referring to Serbia [45,46]. These authors dealt mostly with measuring energy security, but they applied the same methodology, since it was simply evaluation of another set of criteria. The authors claimed that SF-AHP operates with numerical and linguistic data and there is universality of its application concluding to an experimentally verified assessment of energy security and its trend in the future of the natural gas sector.

2.3. Fuzzy Technique for Order Performance by Similarity to Ideal Solution

The basic idea behind the technique for order performance by similarity to ideal solution (TOPSIS) is the use of the heuristic that any candidate decision among all candidates must have the minimum distance from the positive ideal candidate decision and the longest distance from the negative ideal candidate decision [47–49]. Although the method was developed in 1981 [50], it is heavily used for almost every decision-making process, which is based on linguistic variables after the fuzzy extension was proposed [51]. This extension gives the decision maker the ability to define each criterion, its weight, and every decision alternative with triangular based fuzzy numbers as they were defined in (1). Assuming any two fuzzy numbers $\widetilde{M}_1 = (l_1, m_1, u_1)$ and $\widetilde{M}_2 = (l_2, m_2, u_2)$ and using the vertex method for F-TOPSIS, the distance between $\widetilde{M}_1$ and $\widetilde{M}_2$ is given as:

$$d\left(\widetilde{M}_1, \widetilde{M}_2\right) = \sqrt{\frac{1}{3}\left[(l_1 - l_2)^2 + (m_1 - m_2)^2 + (u_1 - u_2)^2\right]} \tag{11}$$

In relation to finding near optimal or suboptimal solutions for the renewable type energy selection problem, lately, there exists some new research [52–57].

Here, we present the step-by-step algorithm of the F-TOPSIS procedure as follows:

Step 1 Define and classify the weights of the criteria involved. Each of the decision maker experts assigns a linguistic weight to all of the predetermined criteria. The assignment is subjective to each expert, but the linguistic values used are similar to a five-Likert scale, which is given in Table 1. Typical values can be "very low importance", "low importance", "medium importance", "high importance" and "very high importance" and the corresponding normalized fuzzy numbers are shown in Table 2.

Table 2. Expert linguistic values and corresponding normalized triangular fuzzy numbers.

Linguistic Value	Normalized Fuzzy Triangular Number
Very low importance	(0,0.1,0.3)
Low importance	(0.1,0.3,0.5)
Medium importance	(0.3,0.5,0.7)
High importance	(0.5,0.7,0.9)
Very high importance	(0.7,0.9,1)

Step 2 Creation of the judgement matrix. The judgement matrix refers to each decision maker and it is constructed by the available alternative decisions D_i in combination with the available criteria C_j.

$$JM = \begin{array}{c} \\ D_1 \\ D_2 \\ \vdots \\ D_n \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_m \end{array} \\ \begin{bmatrix} \widetilde{r}_{11} & \widetilde{r}_{12} & \cdots & \widetilde{r}_{1m} \\ \widetilde{r}_{21} & \widetilde{r}_{22} & \cdots & \widetilde{r}_{2m} \\ \vdots & \vdots & \cdots & \vdots \\ \widetilde{r}_{n1} & \widetilde{r}_{n2} & \cdots & \widetilde{r}_{nm} \end{bmatrix} \end{array} \tag{12}$$

Step 3 Creation of the normalized judgement matrix. To achieve this transformation, we first classify the criteria set into two subsets, namely (a) the benefit criteria (BC) subset and (b) the cost criteria (CC) subset. The normalized judgement matrix NJM is created using JM, BC, and CC where

$$NJM = \begin{bmatrix} \widetilde{x}_{11} & \widetilde{x}_{12} & \cdots & \widetilde{x}_{1m} \\ \widetilde{x}_{21} & \widetilde{x}_{22} & \ldots & \widetilde{x}_{2m} \\ \vdots & \vdots & \ldots & \vdots \\ \widetilde{x}_{n1} & \widetilde{x}_{n2} & \ldots & x_{nm} \end{bmatrix} \quad (13)$$

$$\widetilde{x}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right), \quad j \in BC, \quad \widetilde{x}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right), \quad j \in CC \quad (14)$$

$$c_j^* = max_i\, c_{ij}, \quad j \in BC, \quad a_j^- = max_i\, a_{ij}, \quad j \in CC \quad (15)$$

Step 4 Construct the weighted NJM. The weighted NJM denoted as WNJM is constructed as

$$\widetilde{V} = \left[\widetilde{v}_{ij}\right]_{n\times m} \quad \widetilde{v}_{ij} = \widetilde{x}_{ij}(.)\widetilde{w}_i \quad i = 1\ldots n \quad j = 1\ldots m \quad (16)$$

Step 5 Calculate the fuzzy positive ideal solution (FPIS) and the fuzzy negative ideal solution (FNIS). These solutions are given by the calculation of two vectors respectively A^* and A^- where

$$A^* = \left(\widetilde{v}_1^*, \widetilde{v}_2^*, \ldots, \widetilde{v}_n^*\right) \qquad A^- = \left(\widetilde{v}_1^-, \widetilde{v}_2^-, \ldots, \widetilde{v}_n^-\right) \quad (17)$$

and $\widetilde{v}_i^* = (1, 1, 1)$ and $\widetilde{v}_i^* = (0, 0, 0)$ $i = 1\ldots n$.g

Step 6 Calculate the distance between FPIS and FNIS, that is, the distance between A^* and A^- where

$$\widetilde{d}_i^* = \sum_{i=1}^{n} d\left(\widetilde{v}_{ij}, \widetilde{v}_i^*\right), \quad i = 1\ldots n \quad (18)$$

$$\widetilde{d}_i^- = \sum_{i=1}^{n} d\left(\widetilde{v}_{ij}, \widetilde{v}_i^-\right), \quad i = 1\ldots n \quad (19)$$

Step 7 Calculate the closeness coefficient of each of the alternative decisions and order them in descending order.

$$COEF_i = \frac{\widetilde{d}_i^-}{\widetilde{d}_i^* + \widetilde{d}_i^-} \quad (20)$$

When dealing with the energy suppliers' problem, we must investigate the selection of the best supplier under conditions and criteria. Some authors [58] have claimed that the selection became difficult because in order to choose they needed to achieve the balance between criteria which were not of the same morphological type (i.e., ordinal, cardinal, categorical values, etc.) Therefore, they used the F-TOPSIS method in a two-phase model, with FAHP as the first step, to evaluate and select suppliers. This model could be used as a decision support and making tool since it succeeded to optimize the savings choosing the optimal supplier. In a similar study [59], criteria for solar energy were evaluated, but mostly technological, using intuitionistic fuzzy TOPSIS with a trigonometric entropy vector weight. In addition, another researcher [60] dealt with the renewable energy power deployment in various systems that used electrical power and claimed that the sustainability study of energy storage systems was of critical significance. Therefore, the author did an extensive analysis, evaluation, and ranking of eight criteria in economic, social, environmental, and technological pillars that affected the aforementioned problem. The author initially used the Bayesian best–worst method to determine the weights of the criteria, and then the fuzzy TOPSIS method was used to rank the sustainability performance of different electrochemical energy storage technologies according to the criteria participating in the process. As for the integrating energy type selection planning, a latest work [61] showed the integration of SWOT analysis, SF-AHP, and F-TOPSIS to evaluate energy strategies for energy sustainability. Initially, SWOT was deployed to determine the important factors for sustainable energy planning. Then, SF-AHP was used to calculate the weights of each factor and sub-factor, and in the last step F-TOPSIS ranked the various energy strategies studied. The methodology was very clear and very similar to the proposed methodology in this paper since it guaranteed a systematic approach for energy strategy sustainability evaluation. On the other hand, the same problem was approached with multi-criteria decision-making (MCDM) methods [62]. By using participatory modeling and surveying, the authors identified all relevant criteria that had quantitative and qualitative characteristics and used a decision-making process to calculate the criteria weights [63]. Specifically, SF-AHP was used for the weights, and then fuzzy VIKOR and F-TOPSIS were utilized for result comparisons. Finally, the most proper energy systems in Saudi Arabia were investigated using SF-AHP, fuzzy VIKOR, and F-TOPSIS methods to select the most eligible system among eight alternatives [64]. The priority of the investment for energy systems was computed by doing sensitivity analysis, and pairwise comparison of the alternatives was implemented using the weight of group utility and fuzzy DEA (data envelopment analysis) approaches. The results showed that solar energy was the most productive.

2.4. Fuzzy Goal Programming

Goal programming (GP) is a well-known method introduced by Charnes and Cooper [65] and later on extended by other researchers [66–70]. This methodology aims at optimizing (minimizing) the achievement of a decision relative to the preset goal levels. The mathematical definition of GP is [65]:

$$Min\left(\sum_{i=1}^{K}(p_i+n_i)\right) \qquad s.t. \qquad \begin{array}{ll} (AX)_i+n_i-p_i=b_i & \\ X\in C_s & i=1..K \\ n_i,p_i\geq 0 & \end{array} \tag{21}$$

where $n_i, p_i,\ b_i, X, C_s$ are the set of positive deviations, the set of negative deviations, the preset level of goal, the decision, and the constrains or criteria, respectively. There are many differentiations to the method sometimes focusing on the problem at hand such as: (a) weighted GP (WGP) [68], (b) lexicographic GP (LGP) [71] and (c) MINMAX GP (MGP) [72]. The introduction of fuzzy representation of variables in GP was presented by Narasimhan [73] who created the fuzzy goal programming (FGP) method. This author involved fuzzy subsets to formulate imprecision in defining goals for the decision making.

The problem is a multi-objective and multi constraint problem which consists of the following set of optimization functions along with the rich set of constraints:

$$\begin{array}{ll} Min \displaystyle\sum_{i=1}^{i_0} w_i\frac{p_i}{\Delta_i^R}+\sum_{i=i_0+1}^{j_0} w_i\frac{n_i}{\Delta_i^L}+\sum_{i=j_0+1}^{K} w_i\left(\frac{n_i}{\Delta_i^L}+\frac{p_i}{\Delta_i^R}\right) & \\ s.t.\ (AX)_i-p_i\leq b_i & i=1,\ldots,\ i_0 \\ (AX)_i+n_i\geq b_i & i=i_0+1,\ldots,\ j_0 \\ (AX)_i+n_i-p_i=b_i & i=j_0+1,\ldots,\ k_0 \\ (AX)_i-p_i\leq b_i^u & i=k_0+1,\ldots,\ K \\ (AX)_i+n_i\geq b_i^l & i=k_0+1,\ldots,\ K \\ \mu_\iota+\frac{p_i}{\Delta_i^R}=1 & i=1,\ldots,\ i_0 \\ \mu_\iota+\frac{n_i}{\Delta_i^L}=1 & i=i_0+1,\ldots,\ j_0 \\ \mu_\iota+\frac{n_i}{\Delta_i^L}+\frac{p_i}{\Delta_i^R}=1 & i=j_0+1,\ldots,\ K \\ \mu_\iota,n_i,p_i\geq 0 & i=1,\ldots,\ K \\ X\in C_s & \end{array} \tag{22}$$

Relatively to decision making in energy-oriented problems, lately, there has been substantial research that has utilized various versions of the GP and the FGP methodologies. In other work [74], FGP was adapted to accommodate changes in energy costs and future advances in technology maturity for the type of energy selection problem, in the case of Oregon, USA. This model also took under consideration the preferences of the stakeholders to reveal the costs and benefits of complex decisions regarding renewable energy. In a similar work also presented [75], the authors proposed an FGP model that integrates optimal resource allocation for the development of policies related to setting goals such as the minimization of energy consumption and the reduction of greenhouse emissions, while at the same time there exists economic development for the United Arab Emirates. As for renewable energy, a research [76] applied the FGP methodology to evaluate the policies related to biodiesel production in the Philippines using as objectives the maximization of feedstock production, the overall revenue, and minimization of energy. In that work, we see the innovative involvement of several agricultural, rural, environmental and social criteria and constraints, such as the availability of land, labor, water, and machine time, using fuzzy linguistic values for their representations. Towards this direction, a fairly recent research [77] evaluated suitable sustainable feedstocks considering them as the key factor for the optimum renewable products allocation. Their study proposed a hybrid adaptive framework based on a participatory modeling approach, with a process to produce weights of evaluation criteria and their ranking, using dynamic hesitant fuzzy sets. Each of the criteria sets was assigned a weight based on the dynamic hesitant fuzzy entropy method. Using F-TOPSIS, the criteria were ranked in descending order with respect to the FPIS and the FNIS. However, all policies must base their methodology on the optimal mix of different plant types, where in the country these new plants must be built, and finally, what their capacity should be. According to these additional criteria, from the administrative point of view, the interoperability between the available types of renewable energy plants was analyzed [78], synthesizing a variety of additional factors such as geographical, climatic and ecological. The authors applied the FGP model for the case study of the Algeria focusing on the generation of electricity using renewable energy resources. An increasing number of researchers have conducting similar research referring to their own country territory and this has interested emanates due to the huge economic and environmental advantages accrued by the process [79].

Additional research attempts relating to fuzzy goal programming and energy alternatives, types, and suppliers have also been shown recently. First, on the one hand, a priority-based FGP method was presented [80], to deal with the congestion management problem in electric power transmissions and their formulation was via the use of genetic algorithms to determine the membership functions that correspond to the criteria of their analysis. On the other hand, other authors [81] claimed that hybrid energy systems are the future of earth consisting of different types of conventional and renewable resources. After they categorized these systems into grid and stand-alone, they tried to formulate the total profit obtained by their operation utilizing the ratio of renewable energies with the load demand for consumption using FGP. Additionally, previous research was extended [82] on macroeconomic growth models and introduced new criteria variables for investment into the energy sector for the use case of Kazakhstan. Their method was based on FGP and it contributed significant findings in terms of the impact made by R&D on the long-run economic sustainable growth of Kazakhstan regarding energy decision making. Similarly, in a work for the country of Morocco [83], the author proposed an FGP methodology to calculate a sustainable solution, while keeping in mind the unpredictable fluctuations of price, demand, and uncertainty in the energy sector and more specifically for the biodiesel production. In terms also of other renewable energy types, a recent work [84] investigated the potential of exploiting wind energy in India. More specifically, the authors explored various decision-making approaches in relation to fuzzy analysis with the perspective of justification of major factors that influence the effective use of wind energy. Their findings indicated that India had the maximum potential for taping wind energy via a set of suggested policies that would need to be established to maximize the use of renewable source of energy. Finally, an innovative weighted-additive fuzzy multi-choice goal programming (WA-FMCGP) model was proposed [85], introducing energy relating goals with multiple-choice aspiration levels (MCALs). Although their work was mostly presented as a proof-of-concept, application to energy sector numerical problems could help as a supplementary method, in contrast to the multi-attribute decision making for fuzzy programming and multi-choice goal programming related problems.

2.5. Research Comparison and Novelty of our Approach

In this subsection, we summarize the existed literature depicted in the previous section in a comparative table and we discussion the novelty of our research as compared with the exiting literature. We concentrate only on the research that relates the models of SF-AHP, FGP, and F-TOPSIS to energy (giving focus to renewable energy sector) as the amount of research in the general application of the aforementioned models is beyond limits and out of the scope of this work. Table 3 presents a multitude of popular MCDM fuzzy oriented techniques for sustainable and renewable energy planning related studies.

Table 3. Comparison of research results related to renewable energy selection using stochastic fuzzy analytic hierarchical process (SF-AHP), fuzzy goal programming (FGP), and fuzzy technique for order performance by similarity to ideal solution (F-TOPSIS).

Studies	Case Study	Energy Strategies	Criteria	MCDM Methods	Best Strategy
[52]	Lagos Central District	Numerical illustrations	Energy selection	IF-TOPSIS	Only TOPSIS
[81]	Numerical example of small town	Multiobjective decision via function optimization	Collaboration of multiple energy types	GP	GP
[83]	Numerical example	Biodiesel	classification	FGP	Only one is considered
[62]	Turkey	Select the best energy	Multicriteria	FAHP, F-VICOR, F-TOPSIS	Collaboration
[53]	Turkey	Selection among all, not only renewable	Strengths, opportunities, weaknesses, threats	F-TOPSIS, SWOT, ANP	ANP
[74]	Oregon	Min and max of criteria	Construction cost, Production cost, land use, environmental impact	FGP	FGP
[54]	N/A	Biomass	Profit, sales, customization, affordability, participation, experience, technology	HF-DEMATEL, HF-TOPSIS	HF-TOPSIS
[85]	N/A	Electrochemical energy storage	Economic, social, environmental, and technological	F-TOPSIS, FGP	F-TOPSIS
[55]	Numerical Example	Renewable energy policy selection	Technology, environmental, social, economical	VIKOR, IVPLTS	IVPLTS
[42]	Taiwan	Solar energy	Economic development, energy exploiting, environmental protection	SEA, FDM, SAM, Fuzzy AHP	FAHP
[76]	Philippines	Biodiesel	Max feedstock production and revenue, min of energy used and working capital, availability of land, labor, water and machine time	FGP	FGP
[56,57]	India	Selection between nuclear, solar, hydropower, biomass, heat, and power	Efficiency, investment-operation cost, water pollution, pollutant emission, land, social acceptance, job creation	F-TOPSIS	F-TOPSIS
[56]	India	Determine the potentiality indices for healthier exploration of wind energy resources in India	Wind power density, availability of suitable, land, government initiatives, grid connectivity, technical prowess	TOPSIS VIKOR FAHP	Combination of F-TOPSIS and F-VIKOR

Table 3. *Cont.*

Studies	Case Study	Energy Strategies	Criteria	MCDM Methods	Best Strategy
[61]	Pakistan	Rank 13 energy strategies	Multitude of criteria in MCDM process	SWOT FAHP and F-TOPSIS	Integration of the two methods
[64]	Saudi Arabia	Eight energy strategies as candidates	Power generation, capacity, efficiency, storability, safety, air pollution, net present value	Integrated FAHP F-VIKOR, F-TOPSIS	Solar energy is the most profitable according to both F-VIKOR and F-TOPSIS
[44]	Pakistan	solar, wind, and biomass	4 Basic criteria (economic, environmental, technical, and socio-political), and 17 subcriteria	SWOT FAHP	SWOT FAHP

We claim that our research is novel as compared with the most related (state of the art) research because of the following arguments:

- Most of the research attempts concentrate on a specific MCDM methodology and they do not integrate a plethora of methodologies to produce a "holistic" result based on more than one mode.
- There is not any other research work on the Greek case study to the best of our knowledge.
- Our methodology extends the conventional AHP, GP, and TOPSIS methodologies in terms of integrating the opinions of most critical stakeholder bodies as fuzzy values of their linguistic values in order to solve the MCDM problem of selecting renewable energy sources.
- The proposed methodology explores the validity and applicability of FAHP, FGP, and F-TOPSIS under the existed divergence.
- The only previous research works [62,74] that have some similarity to our methods and findings systematically try to select the best energy type under criteria.

3. Case Study: Thessaly Region, Greece

3.1. Characteristics of the Region and Methodological Roadmap of the Study

Thessaly Region is located in the middle mainland of Greece (see map in Figure 3) extending with a total area of 14,036.64 km^2 and a population of 725,874 inhabitants (2018). Lately, the region exhibits a sharp turn to manufacturing and industrialization from the conventional agricultural activities.

Figure 3. Map of the region of the case study.

Regional sustainability (especially energy sustainability) has become a major concern of competent authorities. It participates in several initiatives in relation to urban planning actions, transition to renewable energies, and boosting of the establishment of solar energy production plants. Following

Europe's post-petroleum actions, most of the regional municipalities initiated several actions towards bio-energy transition, always under the precondition of succeeding economic growth at the same time. Apart from competent authorities, however, this energy conversion depends on the interoperability and the interplay between the regional stakeholders and the various regional social groups.

The methodological organization framework of this work is depicted in Figure 4. Initially, we set the scope of the study, which is the evaluation of low-carbon energy technology alternatives, to select the most suitable for the region under examination. The ultimate goal is the conversion to electricity, the most commonly used energy form. This would provide proof to competent authorities for supporting future policy making. The first step to achieve this goal is to perform the SWOT analysis for establishing all the relevant advantages and disadvantages, as well as any opportunities or threats that can occur due to the decision of choosing an energy alternative. Data for the SWOT analysis comes after selecting the stakeholders, conducting thorough interviews, and organizing all responses setting up all the criteria which they believe that affect the selection. The criteria can be clustered in various categories according to what they refer to. In most of the studies, these criteria are categorized into technological, social, economic, and environmental. Then, the FGP methodology is engaged to find the degrees of memberships of these criteria. We have a bidirectional process of the FGP and FAHP, as seen in Figure 4, as the most important criteria have to be discovered for participating in FAHP, and later in F-TOPSIS. Thus, first, FGP is attended, and then FAHP produces the normalized crisp weight distribution of the criteria. Then, FGP is again involved to provide the degrees of memberships in order to ensure that the selection among all criteria is adequate to provide reliable input for F-TOPSIS. Note, that the criteria are organized for pairwise comparisons based on the FAHP approach that succeeds in ranking them on a predefined importance scale, and therefore weight assignment is possible. Further comparisons between results from FAHP are done after the F-TOPSIS application. Following the FGP, FAHP, and F-TOPSIS application, the policy maker can use the TOWS analysis that can define various strategies attacking the problem at hand.

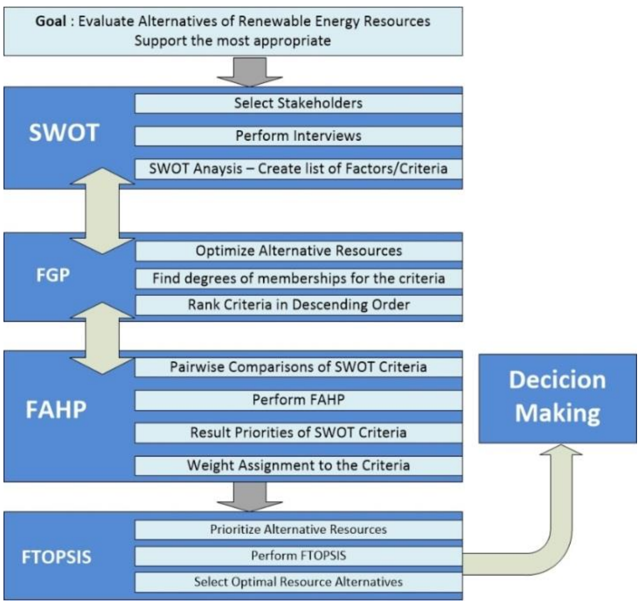

Figure 4. Methodological map in evaluating renewable energies.

3.2. SWOT Analysis

We use the SWOT analysis to strategically integrate all strengths, weaknesses, opportunities, and threats in relation to the energy planning problem.

Recently, many similar studies have been conducted to solve this problem, with typical interests in renewable energy [86], bio-energy [87] and regional energy planning [88,89]. We have utilized 17 experts/stakeholders to set up the SWOT matrix coming from a diverse environment of education, research, government, and energy production utilities according to the recommended expert sampling methodologies [90,91]. The result of their interviews is depicted in Figure 5, where, after amalgamation of similar factors in one, we summarize all the strengths, weaknesses, opportunities, and threats. Following this survey, we asked the experts, in a second stage, to identify all the relevant criteria in selecting one of the candidate types of renewable energy (biofuel, wind, hydro and solar). The interview was conducted under the pre-assumption of clustering these criteria into the aforementioned categories of technological, economic, social, and environmental. The categories of criteria from this survey are shown in Table 4 and the quantification of the stakeholders' importance of these criteria before fuzzification are shown in Figure 6. More specifically, according to the four categories of experts coming from the education, research, government, and energy production utilities sectors, we obtain four average series for the 21 criteria emanated from the survey. The value of each curve is an average evaluation of each criterion from the corresponding stakeholder body.

Figure 5. SWOT analysis, setup of strengths, opportunities, weaknesses, and threats.

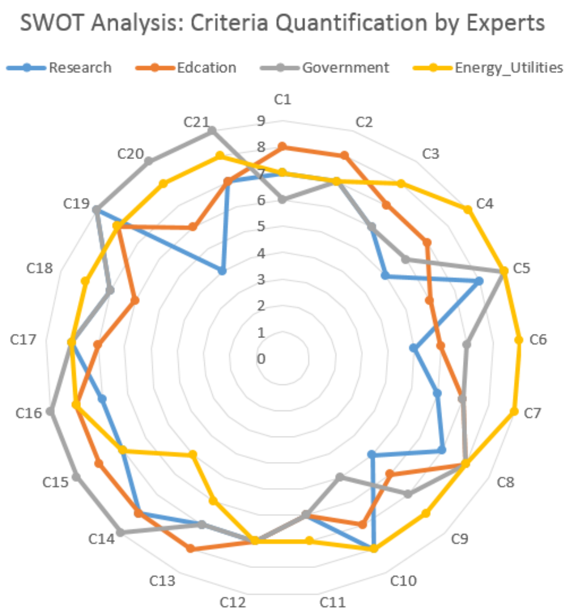

Figure 6. SWOT analysis, criteria quantification by experts before fuzzification.

Table 4. Expert stakeholder criteria setup for the energy type selection.

Criteria No.	Description
	TECHNOLOGICAL
C1	Availability of the technological resources for application of the type
C2	Human capital expertise
C3	Robustness and reliability of the energy type
C4	Electricity supply
C5	Safety
	ECONOMIC
C6	Capital cost
C7	Fuel or energy cost
C8	Life expectancy of the system
C9	Cost to connect to the electricity network
C10	Research and development cost
C11	Marketing and other cost
	ENVIRONMENTAL
C12	Waste production
C13	Hazardous aerial emissions
C14	Ecology preservation
C15	Land use
	SOCIAL
C16	New jobs
C17	Quantification of the (not in my back yard) NIMBY phenomenon
C18	Social perception and acceptance
C19	Impact on residents' everyday life and health
C20	Feasibility of the energy plant
C21	Impact to regional sustainability

Using the previous model, we also apply the TOWS analysis (a reverse approach to SWOT), to identify potential strategies for the problem resolution. The set of strengths, weaknesses, opportunities, and threats, remains the same, but the morphology of the TOWS matrix is altered as to the prioritization of the pairwise strategies chosen. More specifically, we choose the following: (a) To minimize both threats and weaknesses as the strategy of the highest priority, therefore the WT (weakness-threat) as a (min-min) strategy can be used to reduce the threats simultaneously with the overcoming weaknesses and shortcomings; (b) to minimize weaknesses while at the same time try to maximize the opportunities (Strategy WO) to new and well-established energy portfolio alternatives is another promising strategy used in order to mitigate the weakness; (c) Strategy ST (max-min) to maximize the strengths of each alternative energy portfolio while at the same time minimizing the threats and risks taken choosing a specific energy type; and (d) Strategy SO (max-max), the most optimistic approach, to attempt to maximize the strengths while at the same time maximizing the opportunities.

3.3. Fuzzy Goal Programming Analysis

In this section, we provide the mathematical formulation of the use case of Thessaly attacking the problem from the fuzzy goal programming point of view. Policy makers, competent authorities, and regional stakeholders have determined, via the participatory modeling (surveys and focus groups), the criteria for alternative resource energies. Let:

- X_1 be the solar annual electricity generation;
- X_2 be the biofuel annual electricity generation;
- X_3 be the hydro annual electricity generation; and

- X_4 be the wind annual electricity generation.

Note that all aforementioned electricity amounts are in GWh units.

Because the survey participants gave fuzzy evaluations of the criteria above, we also used questions that relate the fuzzy intervals on the hard or approximate values. For example, in relation to criterion C1 (availability of technological resources), participants could easily answer the question "How many technological resources are needed of solar/hydro/wind/biofuel conversion to electricity?" with answers such as "medium", "large", or "low", but could not specify a specific or hard number in such amounts. The idea of specifying intervals (lower and higher thresholds) for set/crisp values on the criteria alleviated the problem. The problem, however, of determining the initial values of the fixed criteria values remains, as it depends on the entity each time. For example, the amount of technological resources is difficult to be determined in moneys as opposed to capital costs or fuel or energy costs. At the same time, wide ranges of intervals initiate higher uncertainties and need to initially go through a sensitivity analysis or need to be predicted accordingly [92,93].

In addition, it is possible to retrieve a solution with adequate results using deviation variables and deviation quantities.

According to international studies [85,94] and the Thessaly Region authorities, the crisp values and the intervals for the criteria under study are given in Table 5.

Table 5. Crisp criteria values and intervals.

Criteria	Solar	Wind	Biofuel	Hydro	Aspiration Level	Tolerance
C1	4,048,112 $\leq y_{11} \leq$ 4,648,112	2,098,741 $\leq y_{12}$ $\leq$ 3,098,741	8,683,567 $\leq y_{13}$ $\leq$ 9,500,000	650,000 $\leq y_{14} \leq$ 750,000	18,000,000	1,000,000
C2	40,481 $\leq y_{21} \leq$ 46,481	82,962 $\leq y_{22} \leq$ 92,962	605,571 $\leq y_{23} \leq$ 645.571	10,000 $\leq y_{24} \leq$ 15,000	6,000,000	600,000
C6	467,925	1,814,470	9,292,500	375,000	41,000,000	4,100,000
C7	N/A	N/A	N/A	N/A	N/A	N/A
C12	14,190	57,178	68,950	52,000	4,000,000	4,000,000
C16	1500 $\leq y_{61} \leq$ 2000	900 $\leq y_{62} \leq$ 1200	500 $\leq y_{63} \leq$ 800	500 $\leq y_{64} \leq$ 800	1500	350

Due to the fact that there is not available data in terms of the criterion C7 (fuel or energy cost), this criterion does not participate in the goal programming calculations. The problem is, then, formulated as an optimization problem that is described by the following goals:

$$\begin{gathered}G_1:\ y_{11}X_1+y_{12}X_2+y_{13}X_3+y_{14}X_4 \leq 18,000,000\\ G_2:\ y_{21}X_1+y_{22}X_2+y_{23}X_3+y_{24}X_4 \leq 6,000,000\\ G_3:\ 467925X_1+1814470X_2+9292500X_3+375,000X_4 \leq 6,000,000\\ G_4:\ 14190X_1+57178X_2+68950X_3+52,000X_4 \leq 18,000,000\\ G_5:\ y_{61}X_1+y_{62}X_2+y_{63}X_3+y_{64}X_4 \leq 1500,\end{gathered} \tag{23}$$

where the variables X represent the solar, wind, hydro, and biofuel conversions to electricity (annual amounts) in GWh.

Assuming the following hard constraints set by the policy makers given by the inequalities:

$$\begin{gathered}X_1+X_2+X_3+X_4 \geq 40\\ X_1+X_3 \geq 22\\ X_2 \geq 12\\ X_3 \geq 10\\ X_4 \geq 10\end{gathered} \tag{24}$$

For the above constraints we can find a variety of solution sets for the variables X_1, X_2, X_3, X_4 (for example, a solution set is 10, 12, 10, 10) can produce a set of membership functions for the fuzzy goal programming model. A set that corresponds to the previous solution set is as follows:

$$(\mu_1, \mu_2, \mu_3, \mu_4, \mu_5) = (0.37,\ 1,\quad 0.45,\ 0.67, 1)$$

Solving the problem with LINGO [95], yields the following near optimal solution for the decision variables and the degree of the membership functions:

$$(X_1, X_2, X_3, X_4) = (17.173256,\ 12,\ 12.826744,\ 10)$$

$$(\mu_1, \mu_2, \mu_3, \mu_4, \mu_5) = (0.99,\ \ 0.99,\ \ 0.99,\ \ 0.67,\ \ 1),$$

showing that the goal, G_4 (membership function degree 0.67), that corresponds to the waste production minimization is not fully achieved.

3.4. Stochastic Fuzzy AHP Analysis

The main objective using AHP is to order the importance of criteria and factors that directly affect the goal of the problem solution. Thus, the prioritization of the criteria weights effectively determines the operational energy measures that a policy maker must take within the scope of energy sustainability in a region. Coming from the SWOT analysis, we have categorized these criteria into technological, economic environmental, and social. For the completion of the reciprocal pairwise comparison matrix in SF-AHP, we followed the method of producing separate matrices for each criteria category instead of a single one. There are two reasons for doing this. The first reason is the introduced bias by the experts, who unconsciously prioritize criteria of their own expertise higher than of other expertise. Secondly, studies have shown that as the number of criteria increases, the accuracy of determining the exact defuzzified value of the importance weight of each criteria decreases [96,97]. Tables 6–9 are depicted in pairs, namely Table 6a,b to Table 9a,b, accordingly. Each of these pair are devoted to each one of the aforementioned criteria categories. Specifically, the (a) part of each table shows the fuzzified pairwise comparison matrix. The second part illustrates the following results: (a) the computation of the fuzzy geometric mean, (b) the final fuzzified value of each criteria using the normalized value its own fuzzy geometric mean, (c) the defuzzified crisp value, and finally (d) the normalized crisp numeric percentage weight of the criteria. The method of calculating the fuzzy geometric mean is introduced by Buckley [98]. More specifically:

- Table 6a shows the calculation of the fuzzified pairwise comparison matrix for the technological category of criteria used in the survey.
- Table 6b shows the technological criteria fuzzy and defuzzified weights.
- Table 7a, above, shows the calculation of the fuzzified pairwise comparison matrix for the economics category of criteria used in the survey, whereas Table 7b, below, shows the economics criteria fuzzy and defuzzified weights computed.
- Table 8a, above, shows the calculation of the fuzzified pairwise comparison matrix for the environmental category of criteria used in the survey, whereas Table 8b, below, shows the environmental criteria fuzzy and defuzzified weights computed.
- And finally, Table 9a, above, shows the calculation of the fuzzified pairwise comparison matrix for the social category of criteria used in the survey, whereas Table 9b, below, shows the social criteria fuzzy and defuzzified weights computed.

Table 6. SF-AHP results per criteria category for the category technological. (**a**) Fuzzified pairwise comparison matrix; (**b**) Criteria fuzzy and defuzzified weights.

(a) Fuzzified Pairwise Comparison Matrix

	C1	**C2**	**C3**	**C4**	**C5**
C1	(1,1,1)	(1,2,3)	(2,3,4)	(2,3,4)	(0.166,0.2,0.25)
C2	(0.333,0.5,1)	(1,1,1)	(6,7,8)	(2,3,4)	(6,7,8)
C3	(0.25,0.333,0.5)	(0.125,0.142,0.166)	(1,1,1)	(0.166,0.2,0.25)	(0.25,0.333,0.5)
C4	(0.25,0.333,0.5)	(0.25,0.333,0.5)	(4,5,6)	(1,1,1)	(1,1,1)
C5	(4,5,6)	(0.125,0.142,0.166)	(2,3,4)	(1,1,1)	(1,1,1)

(b) Criteria Fuzzy and Defuzzified Weights

Fuzzy Geometric Mean	**Lower**	**Middle**	**Upper**	**Crisp**	**Norm Crisp**
(0.9213, 1.2919, 1.6437)	0.1232	0.2145	0.3402	0.2260	0.2123
(1.8877, 2.3618, 3.0314)	0.2524	0.3922	0.6275	0.4240	0.3983
(0.2645, 0.3159, 0.4010)	0.0354	0.0525	0.0830	0.0569	0.0535
(0.7578, 0.8887, 1.0844)	0.1013	0.1476	0.2245	0.1578	0.1482
(1, 1.1632, 1.3184)	0.1337	0.1932	0.2729	0.1999	0.1878

Table 7. SF-AHP results per criteria category for the category economic. (**a**) Fuzzified pairwise comparison matrix; (**b**) Criteria fuzzy and defuzzified weights.

(a) Fuzzified Pairwise Comparison Matrix

	C6	**C7**	**C8**	**C9**	**C10**	**C11**
C6	(1,1,1)	(6,7,8)	(6,7,8)	(7,8,9)	(7,8,9)	(6,7,8)
C7	(0.125,0.142,0.166)	(1,1,1)	(4,5,6)	(4,5,6)	(6,7,8)	(7,8,9)
C8	(0.125,0.142,0.166)	(0.142,0.2,0.25)	(1,1,1)	(3,4,5)	(2,3,4)	(3,4,5)
C9	(1.111,0.125,0.142)	(0.142,0.2,0.25)	(0.2,0.25,0.333)	(1,1,1)	(3,4,5)	(3,4,5)
C10	(1.111,0.125,0.142)	(0.125,0.142,0.166)	(0.25,0.333,0.5)	(0.2,0.25,0.333)	(1,1,1)	(0.25,0.333,0.5)
C11	(0.125,0.142,0.166)	(1.111,0.125,0.142)	(0.2,0.25,0.333)	(0.2,0.25,0.333)	(2,3,4)	(1,1,1)

(b) Criteria Fuzzy and Defuzzified Weights

Fuzzy Geometric Mean	**Lower**	**Middle**	**Upper**	**Crisp**	**Norm Crisp**
(4.6857, 5.2915, 5.8836)	0.4058	0.5233	0.6331	0.5207	0.5127
(2.6367, 2.4183, 2.7495)	0.2283	0.2392	0.2958	0.2544	0.2505
(0.8492, 1.0541, 1.2685)	0.0735	0.1043	0.1365	0.1048	0.1032
(0.5673, 0.6813, 0.8171)	0.0491	0.0674	0.0879	0.0681	0.067
(0.2362, 0.2814, 0.3545)	0.0205	0.0278	0.0381	0.0288	0.0284
(0.3218, 0.3868, 0.4686)	0.0279	0.0383	0.0504	0.0389	0.0383

Table 8. SF-AHP results per criteria category for the category environmental. (**a**) Fuzzified pairwise comparison matrix; (**b**) Criteria fuzzy and defuzzified weights.

(a) Fuzzified Pairwise Comparison Matrix

	C12	**C13**	**C14**	**C15**
C12	(1,1,1)	(1,2,3)	(3,4,5)	(2,3,4)
C13	(0.333,0.5,1)	(1,1,1)	(1,2,3)	(0.333,0.5,1)
C14	(0.2,0.25,0.333)	(0.333,0.5,1)	(1,1,1)	(2,3,4)
C15	(0.25,0.333,0.5)	(1,2,3)	(0.25,0.333,0.5)	(1,1,1)

(b) Criteria Fuzzy and Defuzzified Weights

Fuzzy Geometric Mean	**Lower**	**Middle**	**Upper**	**Crisp**	**Norm Crisp**
(1.5651, 2.2134, 2.7832)	0.2564	0.4892	0.8569	0.5342	0.4698
(0.5774, 0.8409, 1.3161)	0.0946	0.1858	0.4052	0.2285	0.2010
(0.6043, 0.7825, 1.0746)	0.0990	0.1729	0.3309	0.2009	0.1767
(0.5000, 0.6866, 0.9306)	0.0819	0.1517	0.2865	0.1734	0.1525

Table 9. SF-AHP results per criteria category for the category social. (**a**) Fuzzified pairwise comparison matrix; (**b**) Criteria fuzzy and defuzzified weights.

(a)

Fuzzified Pairwise Comparison Matrix

	C16	C17	C18	C19	C20	C21
C16	(1,1,1)	(1,2,3)	(3,4,5)	(1,2,3)	(6,7,8)	(3,4,5)
C17	(0.333,0.5,1)	(1,1,1)	(1,1,1)	(1,2,3)	(2,3,4)	(3,4,5)
C18	(0.2,0.25,0.333)	(1,1,1)	(1,1,1)	(0.25,0.333,0.5)	(1,1,1)	(1,2,3)
C19	(0.333,0.5,1)	(0.333,0.5,1)	(2,3,4)	(1,1,1)	(5,6,7)	(3,4,5)
C20	(0.125,0.142,0.166)	(0.25,0.333,0.5)	(1,1,1)	(0.142,0.166,0.2)	(1,1,1)	(0.333,0.5,1)
C21	(0.2,0.25,0.333)	(0.2,0.25,0.333)	(0.333, 0.5,1)	(0.2,0.25,0.333)	(1,2,3)	(1,1,1)

(b)

Criteria Fuzzy and Defuzzified Weights

Fuzzy Geometric Mean	Lower	Middle	Upper	Crisp	Norm Crisp
(1.9442, 2.7662, 3.4878)	0.2003	0.3776	0.6111	0.3963	0.3615
(1.1225, 1.2988, 1.9786)	0.1156	0.1773	0.3467	0.2132	0.1945
(0.7071, 0.7418, 0.7647)	0.0728	0.1013	0.1340	0.1027	0.0937
(1.2222, 1.6189, 2.2787)	0.1259	0.2210	0.3992	0.2487	0.2269
(0.3379, 0.3979, 0.5054)	0.0348	0.0543	0.0885	0.0592	0.0540
(0.3724, 0.500, 0.6934)	0.0384	0.0683	0.1215	0.0760	0.0694

3.5. Fuzzy TOPSIS Analysis

As explained in the previous section, the norm crisp values for each criterion have been calculated in the SF-AHP process. For the case of F-TOPSIS, we choose to at least use one criterion from each of the categories provided by the participation modeling and the SWOT analysis (categories are: technological, economics, environmental, and social). The one chosen is the one performing with the maximum normalized crisp value obtained from the SF-AHP calculation. To enrich the F-TOPSIS analysis with more criteria, we choose another two out of all performing with the largest of the remaining normalized crisp vales (i.e., C1 and C7). Table 10 is the summary of the normalized fuzzy weights of all participating criteria in the F-TOPSIS.

Table 10. Normalized fuzzy weights of criteria used in fuzzy TOPSIS.

Criteria ID	Lower	Middle	Upper
C16	0.059532	0.168872987	0.416734861
C12	0.076205	0.218783542	0.584356247
C6	0.120609	0.234033989	0.431737589
C2	0.075016	0.175402504	0.427918712
C1	0.036617	0.095930233	0.231996727
C7	0.067854	0.106976744	0.201718494

Table 11 calculates the fuzzy decision matrix and the fuzzy positive ideal solution, as well as the fuzzy negative ideal solution (where H, hydro; S, solar; B, biofuel; W, wind; N, FNIS; and P, FPIS).

Table 11. Calculation of the fuzzy decision matrix and the fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS).

Normalized Fuzzy Decision Matrix Using the c_j^* and a_j^-						
S	(0.555, 0.805, 1)	(0.666, 0.833, 1)	(0.444, 0.592, 1)	(0.444, 0.533, 0.8)	(0.25, 0.444, 1)	(0.777, 0.888, 1)
B	(0.777, 0.888, 1)	(0.777,0.888,1)	(0.444, 0.64, 0.869)	(0.571, 0.695, 1)	(0.25, 0.266, 1)	(0.111, 0.222, 0.333)
H	(0.666, 0.833, 1)	(0.666, 0.833, 1)	(0.444, 0.533, 0.8)	(0.444, 0.5, 0.571)	(0.25, 0.4, 1)	(0.222, 0.444, 0.666)
W	(0.666, 0.805, 1)	(0.666, 0.833, 1)	(0.444, 0.592, 1)	(0.571, 0.727, 1)	(0.25, 0.444, 1)	(0.222, 0.388, 0.666)
Weighted Normalized Fuzzy Decision Matrix						
S	(0.019, 0.076, 0.231)	(0.049, 0.145, 0.427)	(0.053, 0.138, 0.431)	(0.029, 0.056, 0.160)	(0.019, 0.096, 0.584)	(0.045, 0.149, 0.416)
B	(0.028, 0.084, 0.231)	(0.058, 0.155, 0.427)	(0.053, 0.149, 0.374)	(0.038, 0.073, 0.201)	(0.019, 0.057, 0.584)	(0.006, 0.037, 0.138)
H	(0.023, 0.079, 0.231)	(0.049, 0.145, 0.427)	(0.053, 0.124, 0.344)	(0.029, 0.053, 0.114)	(0.019, 0.087, 0.584)	(0.013, 0.074, 0.277)
W	(0.023, 0.076, 0.231)	(0.049, 0.145, 0.427)	(0.053, 0.138, 0.431)	(0.038, 0.077, 0.201)	(0.019, 0.096, 0.584)	(0.013, 0.065, 0.277)
FNIS and FPIS						
N	(0.028, 0.084, 0.231)	(0.058, 0.155, 0.427)	(0.053, 0.138, 0.431)	(0.038, 0.077, 0.201)	(0.019, 0.096, 0.584)	(0.045, 0.149, 0.416)
P	(0.019, 0.076, 0.231)	(0.049, 0.145, 0.427)	(0.053, 0.138, 0.431)	(0.029, 0.056, 0.160)	(0.019, 0.057, 0.584)	(0.006, 0.037, 0.138)

H, hydro; S, solar, B, biofuel; W, wind; N, FNIS; P, FPIS.

Finally, the distance from the FNIS and the FPIS, as well as the ranking of the four energy alternatives is given in Tables 12 and 13, respectively, ranking the solar energy as the best performing with the biofuel as the least performing alternative.

Table 12. Calculation of the distance from FNIS and FPIS.

Distance of Weighted Normalized Fuzzy Decision Matrix from FNIS						
Solar	0	0	0	0	0.02240119	0.174605594
Biofuel	0.006699751	0.007370663	0.033285032	0.026082561	0	0
Hydro	0.002786276	0	0.050800427	0.026688137	0.016916363	0.082897105
Wind	0.002309401	0	0	0.026891263	0.02240119	0.081655598
Distance of Weighted Normalized Fuzzy Decision Matrix from FPIS						
Solar	0.006699751	0.007370663	0	0.026891263	0	0
Biofuel	0	0	0.033651548	0	0.02240119	0.174605594
Hydro	0.003970306	0.007370663	0.050800427	0.052336253	0.005484828	0.093375746
Wind	0.005249127	0.007370663	0	0	0	0.095999878

Table 13. Ranking of the energy alternative types.

Energy Type	$\widetilde{d}_i^*$	$\widetilde{d}_i^-$	CCi = di-/(di- + di *)	RANK
Solar	0.040961676	0.197006784	0.827869306	**1**
Biofuel	0.230658332	0.073438007	0.24149586	**4**
Hydro	0.213338222	0.180088307	0.457743172	**3**
Wind	0.108619668	0.133257452	0.550930373	**2**

$\widetilde{d}_i^*$ and $\widetilde{d}_i^-$ distance between FPIS and FNIS (Equations (18) and (19))

4. Discussion of Results

The FGP methodology is extensively used with the aim to mitigate the ambiguity introduced by the participatory modeling. Unfortunately, the limitation of no availability of set values for the criterion C7 (fuel or energy cost) cannot fully support the translation into fuzzy numbers for all the criteria under concern. However, the results of the GP methodology show a great degree of membership functions for the rest of the participating criteria. Therefore, assuming at least five out of the six criteria are well taken, FAHP was applied for each one of the four criteria categories, based on the results of FAHP as follows:

- For the technological oriented criteria, criteria C2 (human capital expertise) was calculated to be the most important criterion with a normalized crisp weight of 0.3983, with the second in order criterion C1 (availability of the technological resources for application of the type) with a normalized crisp weight of 0.2123. The strategy is to, first, gain the human capital needed to build and manage the energy conversion establishments, and then think about which resources are available. Robustness of the projects is thought to be the least important factor. However, safety and the amount of electricity (GWh) that would be directed to the market are almost equally important criteria.

- For the economically oriented criteria, criteria C6 (capital cost), C7 (fuel and energy cost), and C8 (life expectancy of the system) by far are the most important factors in this specific order, with C6 obtaining a normalized crisp weight of 0.5127 and the other two obtaining weights of 0.2505 and 0.1032, respectively. As expected, the issue of initial capital is the most important factor in investing, especially in such investments of regional level and high cost. The second factor of importance is the energy costs for such factories to operate. Usually, this is calculated as a percentage of the outcome in electricity, but it is a key performance indicator for the overall operation trustworthiness. The lack of obtaining a degree of membership for C7 from the FGP methodology diminishes the trustworthiness of the FAHP method, especially relatively to the outcome of the C7 criterion. However, the value of importance of C7 is still undisputed because of its rating within the category and because of the high score received. Note, for example, that criteria C8, C9, C10, and C11 are all well below the range of 0.10 normalized weight, therefore, we can argue that the rate of C7 within the category cannot be changed and that was the reason that C7 was included in the F-TOPSIS.
- For the environmentally oriented criteria, similarly, clear weight ordering appears in this category with criterion C12 (waste production) performing much higher than the other criteria gaining a normalized crisp weight of 0.4698 and with criterion C13 (hazardous aerial emissions) in second place with a normalized crisp weight of 0.2010, outperforming criteria C14 and C15. The results show that stakeholders want to explore the opportunity to experience green and renewable energy exploitation via policies that minimize the waste production. Moreover, competent authorities and the final policy makers should integrate this approach horizontally and vertically to try to incorporate the appropriate strategic alliances towards low carbon economy.
- For the socially oriented criteria, relative to social acceptance and supportiveness of the low carbon energy policy making, the results of FAHP indicate that the primary factor for the Greek society is the creation of new jobs and how this is going to affect the regional economy with criterion C16 (new jobs) outperforming the other criteria of the category (normalized crisp weight of 0.3615). At the same time, criteria C17 (quantification of the (not in my back yard) NIMBY phenomenon) and C19 (impact on residents' everyday life and health) are almost equally important for the social bodies of Thessaly Region with normalized crisp weights of 0.1947 and 0.2269, respectively. The remaining category criteria participate in the distribution of weights with very low percentages. Thus, although the society wants new jobs and is aware of the health and environmental benefits of the conversion into low carbon practices, people are still afraid to reside close to such energy production plants.

Using the outcomes of SF-AHP, the application of the F-TOPSIS methodology was performed only on the most important criteria of each category, as aforementioned. The method ranks solar energy plants and investments as the most preferable (CC_i of 0.827869306) and wind parks (CC_i of 0.550930373) are ranked second. The substantial difference between the first and second choice is justified by the geographic location of the region and the social perception that solar energy is the least expensive form of producing electricity, while not affecting the environment. However, further investigation has shown that solar energy systems deployment must agree with specific locations. For example, in Thessaly, there are locations in the eastern part, which are more preferable than locations in the western part that occasionally suffers from floods. As to the equipment to be used, there is a need for equipment synchronization in order to become beneficial for the process.

This research offers an original contribution to knowledge by applying a hybrid methodology of three fuzzy MCDM models that can be used as a decision-making tool by competent authorities and investment groups for investing in the energy industry. Using input from the basic pillars of society, the selection of the best renewable energy type fitted in a region is succeeded by the steps of this research paradigm. As it has shown in Sections 3.3–3.5, the amalgamation of the SF-AHP, FGP and F-TOPSIS analyses highlighted the criteria of (a) new job generation, (b) capital cost, (c) availability of technological resources, and (d) waste production, which prevail in the decision-making of competent authorities and private investors when deciding to establish a new energy plant. Thus, the hybrid application of AHP and TOPSIS with the assistance of experts produces a decision-making methodology which can be applicable to the renewable energy industry.

5. Conclusions and Future Challenges

The use of the appropriate form of energy technology is crucial for human society, as it directly affects the regional economy and the industrial and rural development. On top of the critical effects, health and environmental indicators became significant in energy planning decision making, since they affect the sustainable use of regional resources. Therefore, any regional policy making must be focused on designing technologies for the safe management of regional resources and direct investors towards the exploitation of renewable and environment-friendly energy forms.

In this work, we applied the participatory modeling methodology for visioning and strategy development in terms of selecting the most appropriate energy type for regional investments. Available forms were the solar, wind, hydro, and biofuel energy. Initially, a SWOT analysis was performed to mark all the objectives, as well as the internal and external factors that affect the energy form selection process and the establishment of policies to support this selection. The interoperability and interrelationships among the internal and external factors were thoroughly examined. A well-designed effort of polling the public opinion, and most importantly, the stakeholders was also developed via surveys and focus groups. This process highlighted a set of important criteria spanning from technology, economics, environment, and society. Through the interaction between FGP and SF-AHP, we selected the criteria with a high degree of trustworthiness in the process, which are the principal components in the decision-making process, and we calculated the pairwise comparisons matrices making individual runs for each criteria category. This approach provided the most significant criteria/factors according to their normalized crisp weight. The highest weight criterion for each category, as well as the two other criteria with the highest among the rest weights, participated in the F-TOPSIS calculation of ranking the energy types. The result showed that solar energy ranked as the first preference with wind, hydro, and biofuel following, in this order.

Except for the good results emanated from our research, the application of the most popular fuzzy MCDM methodologies such as SF-AHP, FGP, and F-TOPSIS also faced a few, yet memorable limitations, in terms of the planning process, the refinement of fuzzified values, and the combination of the models used [99]. More specifically, the non-existence of budget constraints in the application of the FGP model and the use of budget constraints coming from the literature are a major limitation that leads to doubts in terms of experimental verification of the results of the model. At a second level, on the one hand, involvement of fuzzy modeling always initiates limitations of results as opposed to crisp value measurements. On the other hand, this deficiency is also beneficial in terms of the ability of the stakeholders to express their opinions with linguistic terms as opposed to crisp evaluations. Finally, any use of SF-AHP to find the weights of the criteria used for all the energy alternatives introduces a limitation as to the unidirectional application of only one method as opposed to a comparative approach involving more techniques.

Further investigation must be undertaken for other energy forms and also alternatives. The inclusion of new renewable energy technologies would add confidence in integrated energy policy modeling and decision making. Additionally, a comparative analysis with other fuzzy and soft computing methodologies would also be appropriate to provide a holistic study. Fuzzy cognitive maps, for example, is also a useful tool that could introduce causalities between the criteria, thus, taking into account their interrelations.

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