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An Integrated Approach for Renewable Energy Resource and Plant Location Selection

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ABSTRACT

Renewable energy resources ranking, and power plant location selection are multi-criteria decision-making (MCDM) problems. These problems can be solved as two-phase decision-making tasks separately and sequentially or, in a unified form, as a single-step task. In this paper, we are studying the efficiency and applicability of the unified approach based on fuzzy and Z-information, and TOPSIS technique. Alternatives for the single-step approach are generated based on renewables available in the country and potential geographical locations for these resources. Considering the importance of weights in MCDM and the multiplicity of approaches to criteria weighting, subjective, objective, AHP-based, and combination of the subjective and objective weights are used for decision matrix weighting. Comparative analysis of the solutions, based on various weights, allows making a reliable solution. The results of the study and problem solution confirm the efficiency and applicability of the combined approach. The advantage of the unified single step solution is that this approach, in addition to the solution of the main task, provides to decision-maker additional information about preferable next best renewable and location option as well.

Keywords: Renewables Selection, Multi-criteria Decision, Fuzzy and Z-information, Plant Location Selection, Criteria Weights
JEL Classifications: D81, P48, Q35, Q42

1. INTRODUCTION

The energy sector has rich experience in applying multi-criteria decision-making methods (MCDM) for policy development, planning, resources ranking, plant location selection, and solution of other subject area-specific tasks (Stein, 2013;Soroudi and Turaj, 2013; Kahraman et al., 2015; Kumar et al., 2017; Kaya et al., 2018). Multi-criteria techniques, initially developed for deterministic problems, were, subsequently, with some modifications applied for the solution of the probabilistic and fuzzy tasks.

Energy resources selection/location tasks, depending on the decision-maker's approach, can be analyzed and solved as a two-phase task, or in a unified form, as a single-step task. In the case of the two-phase approach, at the first step decision related to energy resource selection should be done. In the second phase, the decision-maker selects the location of the power units for the resource. The unified approach provides a solution for the resource and location at once. One important difference of the unified approach is that, at the decision matrix composition stage, subject area experts must provide aggregated estimates for the decision matrix elements. These estimates evaluate every available combination of the resource and location. It is necessary to notice, selection of the geographical or administrative region for renewable location is a general solution that should be specified more exactly as a site with precise coordinates.

Publications on renewables and energy resources ranking and selection on the country-level are analyzing different aspects of the problem solution based on various approaches. Cristóbal (2011) has applied based on closeness to the ideal solution VICOR method for renewables project analysis in Spain. Features of the approach is that for every renewable additional alternative are generated, based on power units` capacities. Tasria and Susilawatib

(2014) have applied fuzzy AHP for renewable energy resources selection in Indonesia. Country-specific selection criteria and special procedure for experts' opinion aggregation are used. Hefny et al. (2013) discuss a fuzzy ANP approach using the linguistic variables and Gaussian fuzzy numbers to represent decision-makers' comparison judgments, and extent analysis method to decide the final priority of different decision criteria. Based on research results, it is recommended to decision-makers in the Egyptian government to build more nuclear power stations to cover 25% of the generated electricity in Egypt and to construct solar power stations to cover 5% of the generated electricity. In (Karakaş and Yildiran, 2019) renewable energy alternatives for Turkey are evaluated by using Modified Fuzzy Analytical Hierarchy Process. The evaluation process is based on four main criteria and eight sub-criteria. In this approach reciprocals are evaluated by using negative fuzzy numbers. Hydro, wind, solar, biomass and geothermal energy are analyzed as the renewable energy alternatives. According the results, solar energy is the best alternative, and wind energy is the second-best alternative for Turkey. In another research (Cengiz and Taşkin, 2018), based on fuzzy AHP and fuzzy TOPSIS methods, wind energy was determined as the most suitable energy for Turkey. In this approach, at the first step problem is solved by FAHP and weights, determined at the first step, are used on the second step for formation of the decision matrix for the TOPSIS. Fuzzy AHP is used in (Talinli et al., 2011) for wind farm site selection in Turkey. Four locations are studied with respect to three criteria and fourteen sub-criteria. TOPSIS method is applied in (Nazari et al., 2018) for analysis of four locations and solar farm site selection in Iran. In (Wang et al., 2018) four criteria and twelve sub-criteria are used for evaluation of the seven locations for wind plant locations in Vietnam, based on FAHP and TOPSIS combination. Weights of locations are calculated based on FAHP and these weights are used for determining the final decision on location via fuzzy TOPSIS method. In (Solangi et al., 2019) fourteen cities of Pakistan are studied as potential sites for solar energy projects implementation. The study is based on the use of AHP and fuzzy VICOR methods and the three most suitable locations are selected. AHP is used for criteria weights calculation, the final decision is done based on VICOR.

The brief review of the approaches, used for the problem solution, shows that first of all researchers are applying MCDM based on ideal solution and hierarchy. The methods are used separately or, in combination. Outranking and other methods can be also applied as well.

Multi-criteria decision-making techniques are based on various theoretical foundations, but the most widely used MCDM tools are pairwise comparison, distance-based and outranking methods, and these techniques have different methodological foundations.

The Technique for Order Preference by similarity to ideal solution (TOPSIS), first introduced in (Hwang and Yoon, 1981), is based on the selection of the alternative with the shortest distance from the best and farthest distance from the worst solution. This method has been successfully used in various areas, requiring multi-criteria decision making. The fuzzy version of the TOPSIS, introduced in (Chen, 2000) and elaborated in the follow-up research and publications (Chu, (2002); Mahdavi et al., 2008; Wang and Lee, 2009; Kaya and Kahraman (2011); Madi et al., 2015; Nădăban et al., 2016; Palczewski and Sałabun, 2019), laid down a methodological foundation for applications of the Z-number based versions of the TOPSIS (Yaakob and Gegov, 2015; Krohling et al., 2016; Wang and Mao, 2019).

Based on pairwise comparisons Analytical Hierarchy Process (Saaty, 1977) is one of the most widely used MCDM methods. In AHP decision-maker's judgment is playing a decisive role and fuzzy extensions proposed in (Buckley, 1985; van Laarhoven and Pedrycz, 1983) significantly increased the descriptive power of the approach and solutions relevance. Extensive reviews (Singh et al., 2016; Kaya et al., 2019) are illustrating the applicability and effectiveness of the fuzzy AHP in MCDM in general and in energy resources selection in particular. Z-numbers-based AHP applied in various areas. Zhang (2017) applied this approach for risk ranking in underground construction. Karthika and Sudha (2018) illustrated an application of the Z-numbers-based FAHP for dengue fever risk assessment in various states of India. Yildiz and Kahraman (2020) applied Z-numbers-based fuzzy AHP for social development evaluation and illustrated the applicability of the approach by example.

Energy policy development, planning, resources, and location selection require analysis and evaluation of the finite set of available alternatives with respect to a given set of criteria, in order to select the most appropriate solution in terms of multiple criteria. Distinctive features of this decision-making process are subjectivity, information uncertainty, impreciseness, and incompleteness. In such circumstances as efficient problem-solving tools fuzzy information and Z-number based multi-criteria decision-making methods (MCDM) are used (Kahraman et al., 2015; Krohling et al., 2016; Chatterjee and Kar, 2018; Kaya et al., 2019).

Other features of this decision-making process are that country-level energy policy development, energy resources selection, and plants location decisions have long-run effects, and adjustments and changes of these decisions are very difficult and costly. Moreover, any changes usually have a negative spillover effect on other parties involved into the decisions' implementation process.

For increasing soundness, and reliability of the energy resources selection and plants location decision, in this paper an integrated approach based on Z-TOPSIS has been developed. The approach is based on the fuzzy and Z-information, subjective weights, objective weights, AHP based weights and combination of the subjective and objective weights. The integrated approach provides a combined solution for the renewables ranking, and power plant location.

The remaining part of the paper is set out as follows: In section 2 preliminaries of the fuzzy and Z-numbers, Z-numbers reliability and restriction conversion, Z-numbers based MCDM problem general statement, and basics of the criteria weighting are briefly reviewed. Methodological foundations of the applied methods are presented in section 3. Section 4 describes a country-level application of the integrated approach for the solution of the energy resources selection and plants location task. The conclusion discusses specifics and results of the combined MCDM application for energy resources selection and plants location problem solution.

2. PRELIMINARIES

2.1. Fuzzy and Z-numbers and Operations

In applications, fuzzy numbers with various types of membership functions have been used. The most widely used membership functions are triangular and trapezoidal membership functions (Buckley, 1985; van Laarhoven and Pedrycz, 1983; Chang, 1996). In this paper, we are using trapezoidal and triangular membership functions.

The support M of the trapezoidal fuzzy number (*a, b, c, d*) is {x ∈R I *a*<*x*<*d*} and its membership function $\mu_M(x)$:*R*→[0,1] is equal to

$$\mu_M(x)=\begin{cases}0, & x<a\\ \frac{x-a}{b-a}, & a\le x\le b,\\ 1, & b\le x\le c\\ \frac{d-x}{c-d}, & c\le x\le d,\\ 0, & x>d\end{cases} \quad (1)$$

The support M of the triangular fuzzy number (*a, b, c*) is {x ∈R I *a*<*x*< *c*} and its membership function $\mu_M(x)$:*R*→[0,1] is equal to

$$\mu_M(x)=\begin{cases}\frac{x}{b-a}-\frac{l}{b-a}, x\in[a,b],\\ \frac{x}{b-c}-\frac{c}{b-c}, x\in[b,c],\\ 0 \quad otherwise\end{cases} \quad (2)$$

Basic operations (Chang, 1996) with triangular and trapezoidal fuzzy numbers used in MCDM are presented below:

$$(a_1,b_1,c_1)\oplus(a_2,b_2,c_2)=(a_1+a_2,b_1+b_2,c_1+c_2) \quad (3)$$

$$(a_1,b_1,c_1)\Theta(a_2,b_2,c_2)=(a_1-c_2,b_1-b_2,c_2-a_1) \quad (4)$$

$$(a_1,b_1,c_1)\odot(a_2,b_2,c_2)=(a_1a_2,b_1b_2,c_1c_2) \quad (5)$$

$$(a,b,c)^{-1}\approx(1/c,1/b,1/a) \quad (6)$$

$$(a_1,b_1,c_1,d_1)\oplus(a_2,b_2,c_2,d_2)=(a_1+a_2,b_1+b_2,c_1+c_2,d_1+d_2) \quad (7)$$

$$(a_1,b_1,c_1,d_1)\Theta(a_2,b_2,c_2,d_2)=(a_1-d_2,b_1-c_2,c_1-b_2,d_1-a_2) \quad (8)$$

$$(a_1,b_1,c_1,d_1)\odot(a_2,b_2,c_2,d_2)=(a_1a_2,b_1b_2,c_1c_2,d_1d_2) \quad (9)$$

$$(a_1,b_1,c_1,d_1)\oslash(a_2,b_2,c_2,d_2)=(\frac{a_1}{d_2},\frac{b_1}{c_2},\frac{c_1}{b_2},\frac{d_1}{a_2}) \quad (10)$$

$$(a,b,c,d)^{-1}\approx\left(\frac{1}{d},\frac{1}{c},\frac{1}{b},\frac{1}{a}\right) \quad (11)$$

A Z-number (Zadeh, 2011), **Z**, has two components, Z = ($\tilde{A}$, $\tilde{B}$). The first component, $\tilde{A}$, is a restriction (constraint) on the values which a real-valued uncertain variable, X, can take. The second component, $\tilde{B}$, is a measure of reliability (certainty) of the first component.

As it is shown in (Shahila and Velammal, 2015) and in many other publications, direct computations with Z-numbers, especially in large-scale problems, are complicated, sensitive to the probability density functions, and do not in all cases ensure the successful solution of the task. In applications, an approach based on converting the Z-number to a classical fuzzy number (Kang et al., 2012) can be used.

(a) At the first step reliability of the Z-number B should be converted into a crisp number. There are various approaches to the fuzzy numbers defuzzification. In this paper, for the trapezoidal fuzzy numbers, we are using centroid formulae (Wang et al., 2006)

$$x_0(\tilde{A})=\frac{\int_{-\infty}^{+\infty} x\int_{\tilde{A}}(x)dx}{\int_{-\infty}^{+\infty}\int_{\tilde{A}}(x)dx}=\frac{\int_a^b x\int_{\tilde{A}}^L(x)dx+\int_b^c(x\omega)dx+\int_c^d x\int_{\tilde{A}}^R(x)dx}{\int_a^b\int_{\tilde{A}}^L(x)dx+\int_b^c(\omega)dx+\int_c^d\int_{\tilde{A}}^R(x)dx} \quad (12)$$

$$y_0(\tilde{A})=\frac{\int_0^\omega y(g_{\tilde{A}}^R(y)-g_{\tilde{A}}^L(y))dy}{\int_0^\omega y(g_{\tilde{A}}^R(y)-g_{\tilde{A}}^L(y))dy} \quad (13)$$

Equations (12) and (13) for a general trapezoidal fuzzy number $\tilde{A}$ = [a, b, c, d; ω] can be written as

$$x_0(\tilde{A})=\frac{1}{3}[\frac{-a^2-ba-b^2+c^2+d^2+dc}{(d+c)-(a+b)}] \quad (14)$$

$$y(\tilde{A})=\omega\frac{1}{3}[1+\frac{c-b}{(d+c)-(a+b)}] \quad (15)$$

Accordingly, in case of a triangular fuzzy number

$$x_0(\tilde{A})=\frac{1}{3}(a+b+c) \quad (16)$$

(b) At the second step the weight of reliability should be added to the restriction $\tilde{A}$. The weighted Z-number is denoted as

$$\tilde{Z}^{\alpha} = \{\langle x, \left| \mu_{\tilde{A}^{\alpha}}(x) \right\rangle \quad \left| \mu_{\tilde{A}^{\alpha}}(x) = \mu_{\tilde{A}}(x), x \in [0,1] \right\} \quad (17)$$

(c) Finally, the irregular fuzzy number (weighted restriction) should be converted to a regular fuzzy number

$$\tilde{Z}' = \{\langle x, \left| \mu_{\tilde{A}'}(x) \right\rangle \quad \left| \mu_{\tilde{A}'}(x) = \mu_{\tilde{A}}\left(\frac{x}{\sqrt{\alpha}}\right), x \in [0,1] \right\} \quad (18)$$

$\tilde{Z}'$ and $\tilde{Z}^{\alpha}$ are equal with respect to Fuzzy Expectation.

2.2. Weights in MCDM

The criteria weights are an essential part of the multicriteria task, and they are playing a decisive role in MCDM process. Weights allow to take into account the relative importance of the criteria and regulate a solution process according to decision-maker`s priorities and preferences. Depending on values assigned, these weights can seriously influence problem solution and results. Actually, in multicriteria decision-making, decision maker by means of weights adjusts decision matrix according to own priorities. Given the role of weights in MCDM, decision model developer has to select thoroughly weighting method and weights. There are various methods of determining criteria weights (Roberts and Goodwin, 2002; Pamucar et al., 2018; Odu, 2019) and these methods, depending on information sources and calculation methods, subdivided into three category: subjective weights, objective weights, and combinations of the objective and subjective weights In subjective methods (Point allocation, Direct rating, AHP, Delphi method, SMART etc.) weights are based on experts` opinion or decision makers` judgement, objective weights (Entropy method, Criteria Importance Through Inter-criteria Correlation, Correlation Coefficient and Standard deviation etc.) are derived through mathematical calculations on decision matrix and data array.

Weights can be assigned based on subjective opinion or objective measure. The combination of weights increases the reliability and consistency of the decision. Wang and Lee (2009) present a modification of the fuzzy TOPSIS based on the use of the aggregated subjective and objective weights. Objective weights are determined by the entropy measure. Entropy measure is used in other publications as well (Chatterjee and Kar, 2018; Suh et al, 2019).

Calculations of the weights based on Shannon`s entropy include the following procedures:

(a) Normalization of the aggregated decision matrix

$$\left[Z_{ij}\right]_{mxn} = \left[\frac{Z_{ij}}{\sum_{i=1}^{m} Z_{ij}}\right]_{mxn} \quad (19)$$

(b) Calculation of the entropy measure of each index

$$e_j = -k\sum_{(i=1)}^{m} p_i j \text{ In } (p_{ij}) \text{ where constant } k = (\ln(m))^{-1} \quad (20)$$

(c) Calculation of the divergence of each criteria

$$div_j = 1 - e_j \quad (21)$$

(d) Objective weights calculations

$$W_j^o = {div_j} \Big/ {\sum_j div_j} \quad (22)$$

In case of subjective and objective weights combination, aggregated weight is calculated in accordance with equation (23)

$$W_j^{comb} = \alpha W_j^s + (1-\alpha) W_j^o \text{ where } \alpha \in [0;1\} \quad (23)$$

Parameter α allows the decision maker to regulate individual preference by means of "weighting weights" for subjective or objective approaches.

Subjective weights, used in this paper, are based on linguistic estimates provided by experts for the weight's reliability and restriction.

As it was shown in the introduction, in hybrid approaches weights can be defined based on the AHP method as well.

3. METHODOLOGICAL BACKGROUNDS OF THE METHODS

3.1. Fuzzy and Z-information Based TOPSIS

Fuzzy and Z-information based TOPSIS requires the sequential performance of the following steps:

Step 1: Generation of the subject area-relevant criteria and generalized (resource/location) alternatives.

Step 2: Categorizing criteria as a benefit and a cost criterion.

Step 3: Fuzzy and Z-information based aggregated decision matrix composition.

Step 4: Weights calculation.

Step 5: Converting Z-numbers based decision matrix to fuzzy decision matrix.

Step 6: Normalization of the aggregated fuzzy decision matrix

$$\tilde{z}_{ij}^{\circ} = \left(\frac{a_{ij}}{c_j^+}, \frac{b_{ij}}{c_j^+}, \frac{c_{ij}}{c_j^+}, \frac{d_{ij}}{c_j^+}\right), \; c_j^+ = max_i c_{ij} \left(Benefit\, criteria\right) \quad (24)$$

$$\tilde{z}_{ij}^{\circ} = \left(\frac{a_j^-}{d_{ij}}, \frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right), \; a_j^- = min_i a_{ij} \left(Cost\, criteria\right) \quad (25)$$

Step 7: Calculation of the weighted normalized decision matrix $\tilde{D}_w^{\circ} = \left[\tilde{\vartheta}_{ij}\right]$

$$\tilde{\vartheta}_{ij} = \tilde{z}_{ij}^{\circ} \times \tilde{w}_j \quad (26)$$

Step 8: Determination of the fuzzy positive ideal solution A^+ and fuzzy negative ideal solution A^-.

Step 9: Calculation of the distances of each solution from fuzzy ideal positive and negative solutions:

$$d_i^+ = \sum_{j=1}^{n} d_{\vartheta}(\tilde{\vartheta}_{ij}, \tilde{\vartheta}_j^+) \quad (27)$$

$$d_i^- = \sum_{j=1}^{n} d_\vartheta(\tilde{\vartheta}_{ij}, \tilde{\vartheta}_j^-) \quad (28)$$

Distance between two fuzzy trapezoidal numbers $\tilde{\varphi}_1 = (a_1, b_1, c_1, d_1)$ and $\tilde{\varphi}_2 = (a_2, b_2, c_2, d_2)$ is equal to (Chen et al., 2006)

$$d(\tilde{\varphi}_1, \tilde{\varphi}_2) = \sqrt{\frac{1}{4}((a_1 - a_2)^2 + (b_1 - b_2)^2 + (c_1 - c_2)^2 + (d_1 - d)^2)} \quad (29)$$

Step 10: Calculation of the relative closeness for each alternative:

$$\delta_i = \frac{d_i^-}{(d_i^+ + d_i^-)} \quad (30)$$

Step 11: Alternative ranking in accordance with the relative closeness δ_i, the best alternative has higher closeness coefficient relative to a positive ideal solution.

Step 12: The best alternative selection according to higher priority.

3.2. Fuzzy Analytical Hierarchy Process

In this paper, we are applying fuzzy AHP as an alternative approach for determining weights of criteria used in fuzzy and Z-information based TOPSIS for renewables ranking and power plant locations selection. Fuzzy AHP has been performed as the sequence of the following steps:

Step 1: Problem statement and identification of the alternatives and criteria.

Step 2: Problem hierarchical structure development.

Step 3: Fuzzy description of the classical nine points AHP scale.

Step 4: Matrix representations of the alternatives, and criteria pairwise comparisons.

Step 5: Inputting into pairwise comparison matrix pairwise judgments and reciprocals.

Step 6: Calculations of priorities.

Pairwise comparisons matrixes $\tilde{A}$ are composed based on decision maker`s fuzzy preferences:

$$\tilde{A} = \begin{pmatrix} 1 & \tilde{a}_{12} & \cdots & \tilde{a}_{1n} \\ \vdots & & \tilde{a}_{ij} & \vdots \\ \tilde{a}_{n1} & \tilde{a}_{r2} & \cdots & 1 \end{pmatrix} \quad (31)$$

Geometric mean of each alternative (Buckley, 1985) is used as a mean value of the fuzzy comparisons:

$$\tilde{r}_i = (\prod_{j=1}^{n} \tilde{a}_{ij})^{1/n} \quad (32)$$

A fuzzy weight $\tilde{w}_i$ of criterion *i* is calculated by the formula (29):

$$\tilde{w}_i = \tilde{r}_i \odot (\tilde{r}_1 \oplus \tilde{r}_2 \oplus \ldots \oplus \tilde{r}_n)^{-1} \quad (33)$$

Step 7: Center of area (COA) is used for defuzzification of fuzzy weights:

$$X_{COA} = \frac{\int x \mu_A(x) dx}{\int \mu_A(x) dx} \quad (34)$$

For the triangular fuzzy numbers, it has a simple form:

$$W_i = (a_{w_i} + b_{w_i} + c_{w_i}) / 3 \quad (35)$$

Step 8: Normalization of the weights:

$$W_i^N = W_i / \sum_{i=1}^{n} w_i \quad (36)$$

Step 9: The best alternative selection according to higher priority.

4. APPLICATION FOR RENEWABLE ENERGY RESOURCES SELECTION

As a case, we are analysing renewables ranking and plant location selection task for Azerbaijan. The country`s geographical location and energy resources endowment predetermines three main alternatives for the renewable energy resources that are of interest for production: solar energy, wind, and hydro.

Despite reach endowments by oil and gas, Azerbaijan is gradually increasing share of renewables in energy production and, as it was underlined in the introductory part of this paper, the country is going to increase the share of renewables in energy production up to thirty percent during the next decade.

In spite of the global economic downturn caused by the pandemic and unprecedented declines and fluctuations of the oil and gas prices, the government of the Azerbaijan considers an increase of renewables the share in energy production of the country as a long-term priority in energy policy. At present time pilot projects on construction in the country, 240 MW wind station and 200 MW solar station are elaborated on. In general, it is planned to increase during the next decade share of renewables from the current seven up to thirty percent.

We are applying the combined approach to the renewables ranking and plant location selection. On the country level we can distinguish four regions with distinctive features as potential geographical locations for renewable plants location: Absheron peninsula and Caspian basin area (ACA); Kura-Aras Lowland (KAL); Nakhichevan Autonomous Republic (NAR) area; Mountain and Sub-mountain regions (MSM). Based on renewables available in each region, nine alternatives are identified and these alternatives are analysed with respect to nine criteria: Government policy and regulation (GP&R); Social acceptance; Labour impact; Cost; Spill over effects; Technical efficiency; Technology reliability; Resource availability; Environmental impact.

As a source of information, we are using experts' judgments. Linguistic terms for alternatives and criteria evaluations and their fuzzy descriptions are presented in Table 1. Table 2 represents Z-numbers based evaluations of alternatives with respect to criteria. Table 3 represents fuzzy and crisp restrictions and reliabilities of

Table 1: Codebook of linguistic terms for alternatives and criteria evaluation

Restriction		Reliability	
Linguistic term	Fuzzy value	Linguistic term	Fuzzy value
Very poor (VP)	(0.0,0.0,0.0,0.15)	Very Low (VL)	(0.0,0.0,0.0,0.15)
Poor (P)	(0,0.1,0.15,0.25)	Low (L)	(0,0.1,0.15,0.25)
Below average (BA)	(0.15,0.25,0.35,0.45)	Medium Low (ML)	(0.15,0.25,0.35,0.45)
Average (A)	(0.35,0.45,0.55,0.65)	Medium (M)	(0.35,0.45,0.55,0.65)
Above average (AA)	(0.55,0.65,0.75,0.85)	Medium High (MH)	(0.55,0.65,0.75,0.85)
Good (G)	(0.75,0.85,0.9,1)	High (H)	(0.75,0.85,0.9,1)
Very good (VG)	(0.9, 1,1,1)	Very High (VH)	(0.9, 1,1,1)

Table 2: Z-information based evaluations of alternatives

Alternatives	Criteria								
	C_{11}	C_{12}	C_{13}	C_{21}	C_{22}	C_{31}	C_{32}	C_{41}	C_{42}
Wind ACA	VG, VH	VG, VH	AA, MH	G, H	G, MH	VG, VH	G, H	VG, VH	VG, H
Wind NAR	G, M	G, H	G, H	A, M	AA, MH	VG, H	A, H	AA, H	VG, H
Wind M-SM	A, M	G, M	AA, MH	G, M	A, MH	G, H	A, H	G, MH	VG, H
Solar ACA	G, VH	G, VH	AA, MH	AA, MH	AA, MH	G, VH	G, VH	VG, VH	VG, H
Solar KAL	VG, MH	G, H	AA, H	AA, MH	AA, H	G, VH	AA, VH	VG, H	VG, H
Solar NAR	G, MH	G, H	A, H	A, H	A, H	G, VH	A, VH	AA, H	VG, H
Hydro NAR	A, H	BA, M	G, H	AA, H	G, MH	G, H	AA, H	BA, MH	G, VH
Hydro KAL	BA, H	P, M	G, H	AA, H	AA, MH	G, H	A, H	BA, MH	G, VH
HydroMSM	BA, H	A, MH	AA, MH	A, H	AA, H	G, H	A, H	A, H	G, H

Table 3: Codebook of linguistic terms for criteria weights evaluation

Linguistic term	Restriction (fuzzy value)	Reliability (fuzzy value)	Reliability (crisp value)
Very low (VL)	(0.0,0.0,0.2)	(0.0,0.0,0.2)	0.2582
Low (L)	(0.05,0.2,0.35)	(0.05,0.2,0.35)	0.4472
Medium low (ML)	(0.2,0.35,0.5)	(0.2,0.35,0.5)	0.5916
Medium (M)	(0.35,0.5,0.65)	(0.35,0.5,0.65)	0.7071
Medium high (MH)	(0.5,0.65,0.8)	(0.5,0.65,0.8)	0.8062
High (H)	(0.65,0.8,0.95)	(0.65,0.8,0.95)	0.8944
Very high (VH)	(0.8, 1.0,1.0)	(0.8, 1.0,1.0)	0.9661

Table 4: Codebook of linguistic terms for the criteria and alternatives comparisons

Scale	Definition (linguistic term)	Fuzzy value	Reciprocal
1	Equal importance	(1, 1, 1)	(1,1,1)
3	Moderate importance of one over another	(2, 3, 4)	(1/4, 1/3, 1/2)
5	Strong importance	(4, 5, 6)	(1/6, 1/5, 1/4)
7	Very strong importance	(6, 7, 8)	(1/8, 1/7, 1/6)
9	Extreme importance	(9, 9, 9)	(1/9, 1/9, 1/9)
2, 4, 6, 8	Intermediate values between the two adjacent judgements	(1, 2, 3)	(1/3, 1/2, 1/1)
		(3, 4, 5)	(1/5, 1/4, 1/3)
		(5, 6, 7)	(1/7, 1/6, 1/5)
		(7, 8, 9)	(1/9, 1/8, 1/7)

Table 5: Experts` opinion and Z-numbers based criteria weights (subjective)

Criteria	Converted and aggregated weights (fuzzy)			Defuzzified	Normalized
	a	b	c		
GP&R	0.58136	0.85867	0.96609	0.80204	0.17440
Social acceptance	0.11832	0.29767	0.58136	0.33245	0.07229
Labor impact	0.03536	0.15391	0.31304	0.16743	0.03641
Cost efficiency	0.45962	0.74910	0.96609	0.72494	0.15763
Spillover effects	0.02236	0.15149	0.29068	0.15484	0.03367
Technical efficiency	0.24749	0.41598	0.58136	0.41494	0.09023
Technology reliability	0.17888	0.29673	0.45962	0.31174	0.06779
Resource availability	0.62797	0.87770	0.96609	0.82395	0.17916
Environmental impact	0.71552	0.91830	0.96609	0.86664	0.18844

the linguistic terms used for the criteria weights evaluation. Table 4 represents linguistic terms and fuzzy values used for the criteria and alternatives comparisons. Table 5 represents criteria weights based on expert`s opinion. Table 6 represents subjective, objective, combined, and AHP based evaluation of criteria weights. As it was mentioned earlier, we are using Fuzzy AHP based weights as well (Table 7).

Pair-wise comparison codebook for the fuzzy AHP is designed according to definitions and scale given in (Saaty, 1977).

As it was underlined in 2.2, the weighting is a powerful tool that allows to regulate priorities of decision-maker and indirectly influence best solution search process and results. Variations of the weights, in addition to changes of the indicators, could change a ranking of the alternatives altogether. Therefore, it is useful to study how various approaches to weights selection and changes of weights are influencing multi-criteria solutions.

Since we are used for problem solution subjective, objective, combined, and AHP based weights, four different decision matrices were composed. Each fuzzy decision matrix composed for the TOPSIS, in case of trapezoidal fuzzy numbers, has 324 entries.

In this paper we studied the influence of subjective, objective, combined, and AHP based weights on renewable energy resources

Table 6: Criteria weights

Criteria	Subjective weight	Objective weight	Combined weight	AHP based weight
GP&R	0.1744	0.0400	0.1072	0.0604
Social acceptance	0.0723	0.18998	0.1311	0.0092
Labor impact	0.0364	0.0216	0.0290	0.0277
Cost efficiency	0.1576	0.1493	0.1534	0.2277
Spillover effects	0.0337	0.0959	0.0648	0.0582
Technical efficiency	0.0902	0.1526	0.1214	0.1170
Technology reliability	0.0678	0.1219	0.0949	0.0653
Resource availability	0.1792	0.1006	0.1399	0.3453
Environmental impact	0.1884	0.1278	0.1581	0.0882

Table 7: AHP based criteria weights and ranking

Criteria	Weight	S-ACB	S- KAL	S- NAR	W- ACB	W-NAR	W-MSM	H-NAR	H- KAL	H- MSM
GP&R	0.0604	0.0136	0.0077	0.0082	0.0082	0.0073	0.0073	0.0027	0.0026	0.0028
Social acceptance	0.0092	0.0017	0.0017	0.0017	0.0010	0.0010	0.0010	0.0005	0.0005	0.0005
Labor impact	0.0277	0.0033	0.0037	0.0047	0.0054	0.0033	0.0032	0.0013	0.0014	0.0014
Cost efficiency	0.2277	0.0199	0.0199	0.0291	0.0352	0.0136	0.0143	0.0394	0.0394	0.0167
Spillover effect	0.0582	0.0082	0.0082	0.0082	0.0082	0.0082	0.0082	0.0029	0.0029	0.0029
Technology availability	0.1180	0.0179	0.0128	0.0120	0.0171	0.0101	0.0120	0.0120	0.0139	0.0095
Technology reliability	0.0653	0.0060	0.0085	0.0115	0.0115	0.0025	0.0029	0.0103	0.0107	0.0051
Renewables availability	0.3453	0.0619	0.0520	0.0340	0.0567	0.0184	0.0251	0.0185	0.0571	0.0218
Environmental impact	0.0882	0.0182	0.0169	0.0120	0.0010	0.0079	0.0087	0.0056	0.0041	0.0049
Alternative weights		0.1506	0.1314	0.1213	0.1532	0.0722	0.0827	0.0933	0.1326	0.0659
Normalized weights		0.1501	0.1310	0.1209	0.1528	0.0720	0.0825	0.0930	0.1322	0.0657
AHP ranking		2	4	5	1	8	7	6	3	9

Table 8: Renewables and locations evaluations (TOPSIS)

Renewable and Location	Subjective weights			Objective weights			Combined weights			AHP based weights		
	d_i^+	d_i^-	δ_i	d_i^+	d_i^-	δ_i	d_i^+	d_i^-	δ_i	d_i^+	d_i^-	δ_i
W-ACB	0.089	0.407	0.820	0.214	0.577	0.729	0.193	0.553	0.742	0.174	0.755	0.813
W-NAR	0.309	0.363	0.540	0.319	0.404	0.559	0.358	0.36	0.501	0.313	0.741	0.703
W-MSM	0.379	0.297	0.439	0.389	0.339	0.465	0.452	0.333	0.424	0.343	0.681	0.665
S-ACB	0.112	0.397	0.780	0.195	0.532	0.732	0.253	0.486	0.658	0.16	0.751	0.825
S-KAL	0.134	0.365	0.732	0.237	0.497	0.677	0.276	0.446	0.617	0.184	0.727	0.798
S-NAR	0.248	0.317	0.561	0.302	0.422	0.583	0.371	0.387	0.51	0.317	0.714	0.693
H-NAR	0.405	0.237	0.369	0.479	0.278	0.368	0.533	0.345	0.393	0.481	0.795	0.623
H-KAL	0.447	0.233	0.343	0.543	0.288	0.346	0.552	0.315	0.363	0.487	0.801	0.622
H-MSM	0.383	0.358	0.483	0.407	0.347	0.460	0.442	0.351	0.443	0.401	0.708	0.638

Table 9: Alternatives and locations ranking

Weights	W-ACB	W-NAR	W-MSM	S-ACB	S-KAL	S-NAR	H-NAR	H-KAL	H-MSM
Subjective	1	5	7	2	3	4	8	9	6
Objective	2	5	6	1	3	4	8	9	7
Combined	1	5	7	2	3	4	8	9	6
AHP-based	2	4	6	1	3	5	8	9	7
AHP ranking	1	8	7	2	4	5	6	3	9

alternatives ranking and energy plants location selection via fuzzy TOPSIS techniques. In our study, we assumed that in case of the combination of the subjective and objective weights, both are equally important and weight α in equation (13) is equal to 0.5. Problem solution results are presented in Tables 8 and 9.

According to the results, in the case of Azerbaijan wind and solar energy resources have higher priority, and wind as a renewable resource in our solutions is slightly outperforming solar energy. The most suitable location for the wind plant is the ACB area. In overall evaluation difference between wind and solar is very small and, moreover, if the country is going to significantly increase renewable energy production, solar energy, due to its greater resource potential, gains an additional advantage. Next, the best option is the KAL region with its reach solar energy capacities. Taking into account the closeness of the wind and solar energy resources rankings and ACB and KAL locations, for the Azerbaijan development of both of these resources in the ACB area in the combination of the solar plants construction in KAL can be considered as one of the best options, moreover, this option is laying down the certain foundations for resolving reliability and decoupling issues in energy supply.

5. CONCLUSION

The integrated approach to renewable energy resources ranking and plant location selection provides a unified solution to the problem. Fuzzy information and Z-numbers-based TOPSIS model allow to make up for the deficiency of the quantitative data in the decision-making process, to formalize impreciseness, uncertainties and information incompleteness inherit to energy policy development and planning problem. For a country level energy resources ranking and selection task, four different solutions based on various criteria weighting options are derived. These solutions are based on subjective weights, objective weights, combination of the subjective and objective weights, and weights, derived from the fuzzy AHP-model. Differences in weights assignment approaches are influencing interim calculations results like entering, leaving, net flows, distance to ideal solutions, and closeness but ranking order in solutions are approximately the same, and sensitivity of the solutions to the changes of the criteria weighing methods is moderate. The rank differences for the top three resource/location combinations within each rank does not exceed one point.

According to research findings, the wind is the best option for further development of the country`s energy sector and the next best option is solar energy. From energy resources supply reliability and diversity standpoint, in the case of Azerbaijan, the development of both renewables-wind and solar is the best option.

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