Sustainable Energy Source Selection for Industrial Complex in Vietnam: A Fuzzy MCDM Approach

NGUYEN VAN THANH [ID]

Faculty of Commerce, Van Lang University, Ho Chi Minh City 70000, Vietnam

e-mail: thanh.nguyenvan@vlu.edu.vn

ABSTRACT Shifting from fossil energy to renewable energy is considered an inevitable trend to limit greenhouse gas emissions, protect the environment and reduce dependence on fossil fuels. In that trend, many companies globally, especially multinational corporations with great influence have pioneered the use of clean energy. The fact that more and more companies are committing to renewable energy and taking specific actions to accelerate the transition to clean energy sources is considered a good sign in the joint efforts of the whole world towards a greener future. In Vietnam, the use of renewable energy in production and business activities for sustainable development is also increasingly interested by businesses. Recently, many businesses are interested in taking advantage of renewable energy sources, aiming for environmentally friendly solutions to create products that meet green standards, increasing competitiveness in the market. However, the selection of a suitable energy resource for each industrial complex project is not a simple task as this involve multiple quantitative and qualitative criteria. In this research, the author proposed a fuzzy multicriteria decision making model (F-MCDM) for sustainable energy source selection for industrial complex in Vietnam, utilizing Spherical fuzzy Analytic Hierarchy Process (SF-AHP) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). The main contribution of this study is to propose a Spherical fuzzy MCDM model to support planners and decision makers in the renewable energy resources evaluation and selection process of industrial complexes development projects in Vietnam. A case study is also performed to showcase the feasibility of the proposed approach.

INDEX TERMS Renewable energy, SF-AHP, TOPSIS, FMCDM, sustainable.

I. INTRODUCTION

Foreign direct investment (FDI) plays an important part in the ongoing development of the socio-economic of Vietnam as a developing country. Industrial complexes, also called industrial zones, play an important part in the attraction of FDI, especially for hi-tech industries. After Vietnam joined the World Trade Organization (WTO) in 2007, the country has been rapidly integrating into the international economy and, consequently, numerous industrial complexes have been planned and constructed [1]. As of 2020, Vietnam has 291 industrial complexes which is currently operating, and 272 more are planned to be constructed in the next few years [2]. Sustainability is an important factor to be considered when planning industrial complexes, since environmental protection and social responsibility are important to not only the local government and communities, but also

The associate editor coordinating the review of this manuscript and approving it for publication was Francisco J. Garcia-Penalvo [ID].

for the FDI enterprises who must comply to various local and international regulations [3].

According to Chen *et al.*, environmental factors such as air pollution, climate change performance, renewable resources, etc. are common when consider sustainable location selection of manufacturing facilities [4]. While there are many factors that influence the sustainability of an industrial complex, significant improvement can be made by using sustainable energy resources. Vietnam has a diverse selection of traditional energy sources such as fossil fuel and hydropower, as well as great potential for many sustainable energy resources such as wind, solar, wave, and biomass energy (Tab. 1). Major sustainable energy projects have been approved in the past decade as the Vietnamese government is pushing increase the output of renewable energy to cope with the increase in domestic demand [5]. The government also encourages the development of eco-industrial park and considers sustainable industrial complexes the cornerstone for the sustainability of Vietnam's industrial growth [6].

TABLE 1. Vietnam's renewable energy capacity [5].

Renewable energy source	Installed capacity (MW)	Potential ouput (MW)
Small hydropower	1648	7000 (technical)
Wind	189.2	26763 (technical)
Biomass	270	318630 (theoretical)
Solar	8	7140 (commercial)

However, the selection of a suitable energy resource for each industrial complex project is not a simple task. Planners must take into consideration various quantitative and qualitative criteria when evaluating potential energy sources in order to select the optimal renewable energy option. In this research, the author will consider the renewable energy selection problem of industrial complex projects in Vietnam under fuzzy decision-making environment.

The ordinary fuzzy sets were first introduced by Zadeh [7] and have been applied in many research fields. Over the years, researchers have introduced several extensions of the original fuzzy sets such as Type-2 fuzzy sets [8], Intuitionistic fuzzy sets [9], Hesitant fuzzy sets [10], Pythagorean fuzzy sets [11], and Neutrosophic sets [12]. These fuzzy sets extensions have been widely utilized in solving multicriteria decision-making problems in recent years. Spherical fuzzy sets were recently introduced by Gundogdu and Kahraman [13] based on the idea that the hesitancy of a decision maker can be determined independently from membership and non-membership degrees. This allows decision makers to generalize other fuzzy sets extensions.

The aim of the research is the development of an Multicriteria decision making (MCDM) model based on Spherical fuzzy Analytic Hierarchy Process (SF-AHP) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to support planners and decision makers in the renewable energy resources evaluation and selection process of industrial complexes development projects in Vietnam. The application of Spherical fuzzy sets renewable energy sources selection problem, which allows the independent identification of membership parameters with larger domains, is the main theorical contribution of this research.

II. LITERATURE REVIEW

MCDM models have been widely applied to support decision makers to solve decision-making problems in many industries, such as supplier evaluation and selection [14]–[17], facility location selection [18]–[21], renewable energy project development [22], [23], and technology evaluation [24], [25]. Many of these studies incorporate fuzzy sets theory into MCDM methods to create fuzzy MCDM models which allow these models to perform under uncertain decision-making process [26]–[28].

Ceren Erdin and Gokhan Ozkaya [29] developed a multi-criteria decision-making technique (MCDM) for evaluating and selecting sites that provide ÉLimination et Choix Traduisant la REalité (ÉLECTRE) -based renewable energy sources such as solar, wind, hydropower, geothermal, and biomass. The necessity of sustainable renewable energy sources has been demonstrated by research; as a consequence of the study, the most appropriate energy sources are offered based on the region's geographical position and energy potential. The study's goal is to educate energy firms and renewable energy participants about Turkey's renewable energy potential. Hazem U. Abdelhady et al [30] created a detailed optimization model to find the set of small non-Storage Hydropower plants (SHP) along a particular river reach. The model is based on a greedy evolutionary algorithm that seeks to maximize net yearly benefit. According on the research findings, the model identified seven potential projects through application at the Mamquam River in Canada and the Guder River in Ethiopia. Furthermore, the model suggests 19 possible SHPs that might generate a 62% larger yearly net benefit than the prior research findings. Priyabrata Adhikary et al [31] presented the multi-criteria approach (MCDA) in supporting decision-making for decision-makers during the planning and development of small hydropower projects. S Suryadimal et al [32] utilized the Analytic Hierarchical Process (AHP) approach to assess the feasibility of a hydroelectric power project investment proposal. In the decision-making process, the findings of this study are utilized to determine whether to approve or reject the power plant investment proposal. Proposed plans will serve as references in operating each business stage, allowing for methodical and practical labor while also facilitating oversight and control. The conclusion leads to eight factors that provide major determinants and priority in analyzing potential preparation outcomes, resulting in a standard and right selection. Buket Karatop et al [33] weighted the relevance of renewable energy sources using Fuzzy Analytical Process (F-AHP) and Evaluation Based on Distance from Average Solution (EDAS) approaches. To examine investments in Turkey's renewable energy projects, the Fuzzy Failure Mode and Effect Analysis (F-FMEA) was used to identify the hazards of renewable energy options. According to the conclusions of the study, Turkey should prioritize wind energy in its renewable energy initiatives.

Using the Model of the Spherical Fuzzy, Van Thanh Nguyen et al [34] suggested a decision-making model based on spherical fuzzy sets to pick wind turbine vendors in wind energy projects in Vietnam. The Analytic Hierarchy Process (SF-AHP) was used to establish the weight of the selection criteria, and the Weighted Aggregated Sum Product Assessment (WASPAS) approach was used to rank them. The study's findings may be utilized as a resource for experts in other nations looking for acceptable wind turbine

providers, as well as in quantitative renewable projects. In Thessaly Region, Greece, Constantine Kokkinos and Vayos Karayannis [35] used the SF-AHP approach and the Fuzzy Technique for Order Performance by Similarity to Ideal Solution (F-TOPSIS) to analyze a variety of energy choices, including biofuels, solar, hydroelectricity, and wind energy. The SF-AHP examined all of the criterion categories independently in this study and chose the most important category representative. Finally, F-TOPSIS analyzed these criteria by ranking the energy types in descending order of optimal solution: sun, biofuel, hydro, and wind. Chia-Nan Wang et al [36] utilized the SF-AHP technique and WASPAS to rank offshore wind power station building locations in Vietnam. The sensitivity analysis and comparison analysis results show that the decision framework is practical and resilient. The assessment criteria and technique proposed in this paper can serve as a theoretical foundation for advances in offshore wind energy and coastal development. Yasir Ahmed Solangi et al [37] used the AHP approach to evaluate and prioritize renewable energy hurdles and sub-barriers. The F-TOPSIS approach is then used to evaluate options for the long-term application of renewable energy technology. The AHP approach results show that the most crucial hurdles to the implementation of renewable energy technology are "Economic & Financial," "Political & Policy," and "Market". Sonal Sindhu et al [38] incorporated two Multi-Criteria Evaluation (MCE) methods: the AHP and the F-TOPSIS. According to research, the best site for solar installation is Rohtak, followed by Chandigarh, Gurgaon, and Hisar in the Indian state of Haryana. The investigation's goal is to propose an effective, efficient, and systematic decision support framework that policymakers in India may use to evaluate acceptable solar farm site selection.

III. METHODOLOGY

The Fuzzy MCDM procedure creates a renewable energy sources selection problem model, as shown in the steps and diagram (see Fig. 1).

Step 1: Problem identification

Firstly, the sets of criteria that are influential in renewable energy sources selection problem are defined by experts and when reviewing the literature.

Step 2: Apply spherical fuzzy AHP

The individual criteria weightings in the second evaluation stage are determined by the spherical fuzzy AHP model.

Step 3: Applying TOPSIS model for Alternative Determination

TOPSIS is based on the concept that the chosen alternative should have the shortest geometric distance from the positive ideal solution (PIS) and the longest geometric distance from the negative ideal solution (NIS).

A. SPHERICAL FUZZY SETS THEORY

The principle of spherical fuzzy sets has been used in several MCDM models. Sharaf [39] used spherical fuzzy sets in conjunction with the VIKOR approach to address a supplier
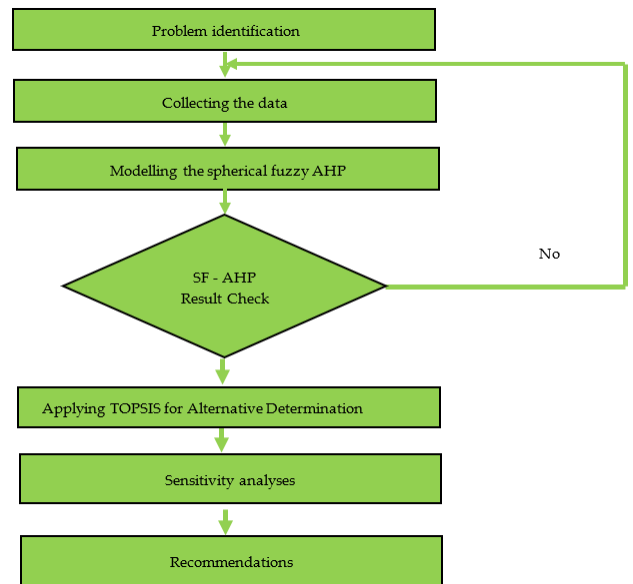

FIGURE 1. Research graph.

selection problem. The use of spherical fuzzy sets offers decision makers with a bigger preference domain. Otay and Atik [40] develop an MCDM model to tackle a real-world oil station site evaluation problem utilizing spherical fuzzy sets and the WASPAS approach. Sensitivity analysis revealed that the suggested model is robust. Gül [41] created a spherical fuzzy variant of the DEMATEL approach. The suggested approach was used to a building contractor selection problem. In this study, a hybrid SF-AHP and CoCoSo technique is designed to handle a DC placement selection problem.

Gundogdu and Kahraman [13] have developed Spherical fuzzy sets theory based on Pythagorean fuzzy sets [42] and Neutrosophic sets theories [43]. The membership functions of Pythagorean fuzzy sets are specified by membership, non-membership, and hesitation parameters. While membership functions in Neutrosophic fuzzy sets also include truthiness, falsity, and indeterminacy factors. The theory of spherical fuzzy sets is founded on the concept that decision makers can generalize different forms of fuzzy sets by establishing a membership function on a spherical surface [44].

A spherical fuzzy set's membership function is determined by three parameters: the degree of membership, the degree of non-membership, and the degree of hesitant. Each of these parameters can have a value between 0 and 1, and the total of their squared values can be no greater than 1.

A spherical fuzzy set $\tilde{A}_S$ of the universe U_1 is defined as follows:

$$\tilde{A}_D = \left\{ x, \left(\mu_{\tilde{A}_D}(x), v_{\tilde{A}_D}(x), \pi_{\tilde{A}_D}(x) \right) | x \epsilon U_1 \right\} \quad (1)$$

with:

$$\mu_{\tilde{A}_D}(x) : B_1 \rightarrow [0, 1], v_{\tilde{A}_D}(x) : B_1 \rightarrow [0, 1],$$
$$\text{and } \pi_{\tilde{A}_D}(x) : B_1 \rightarrow [0, 1]$$

and

$$0 \le \mu^2_{\tilde{A}_D}(x) + v^2_{\tilde{A}_D}(x) + \pi^2_{\tilde{A}_D}(x) \le 1 \quad (2)$$

with $\forall x \in U_1$

$\mu_{\tilde{A}_D}(x)$ represents the degree of membership, $v_{\tilde{A}_D}(x)$ represents the degree of non-membership, and $\pi_{\tilde{A}_D}(x)$ represents x reluctance to $\tilde{A}_D$.

Gundogdu and Kahraman [44] define and show basic arithmetic operations of spherical fuzzy sets, such as union, intersection, addition, multiplication, and power. For these spherical fuzzy sets, $\tilde{A}_D = (\mu_{\tilde{A}_D}, v_{\tilde{A}_D}, \pi_{\tilde{A}_D})$ and $\tilde{B}_D = (\mu_{\tilde{B}_D}, v_{\tilde{B}_D}\pi_{\tilde{B}_D})$, fundamental arithmetic operations are done as follows:

$$\tilde{A}_D \cup \tilde{B}_D$$
$$= \left\{ max\left\{ \mu_{\tilde{A}_D}, \mu_{\tilde{B}_D} \right\}, min\left\{ v_{\tilde{A}_D}, v_{\tilde{B}_D} \right\}, \right.$$
$$min\left\{ \left[1 - \left(\left(max\left\{ \mu_{\tilde{A}_D}, \mu_{\tilde{B}_D} \right\} \right)^2 \right. \right. \right.$$
$$\left. \left. \left. + \left(min\left\{ v_{\tilde{A}_D}, v_{\tilde{B}_D} \right\} \right)^2 \right) \right]^{0.5}, max\left\{ \pi_{\tilde{A}_D}, \pi_{\tilde{B}_D} \right\} \right\} \right\} \quad (3)$$

$\tilde{A}_D$ and $\tilde{B}_D$ intersection:
$$\tilde{A}_D \cap \tilde{B}_D$$
$$= \left\{ min\left\{ \mu_{\tilde{A}_D}, \mu_{\tilde{B}_D} \right\}, max\left\{ v_{\tilde{A}_D}, v_{\tilde{B}_D} \right\}, \right.$$
$$max\left\{ \left[1 - \left(\left(min\left\{ \mu_{\tilde{A}_D}, \mu_{\tilde{B}_D} \right\} \right)^2 \right. \right. \right.$$
$$\left. \left. \left. + \left(max\left\{ v_{\tilde{A}_D}, v_{\tilde{B}_D} \right\} \right)^2 \right) \right]^{0.5}, min\left\{ \pi_{\tilde{A}_D}, \pi_{\tilde{B}_D} \right\} \right\} \right\} \quad (4)$$

$\tilde{A}_D$ and $\tilde{B}_D$ have been added:
$$\tilde{A}_D + \tilde{B}_D = \left\{ \left(\mu^2_{\tilde{A}_D} + \mu^2_{\tilde{B}_D} - \mu^2_{\tilde{A}_D}\mu^2_{\tilde{B}_D} \right)^{0.5}, \right.$$
$$\times v_{\tilde{A}_D}v_{\tilde{B}_D}, \left(\left(1 - \mu^2_{\tilde{B}_D} \right) \pi^2_{\tilde{A}_D} \right.$$
$$\left. \left. + \left(1 - \mu^2_{\tilde{A}_D} \right) \pi^2_{\tilde{B}_D} - \pi^2_{\tilde{A}_D}\pi^2_{\tilde{B}_D} \right)^{0.5} \right\} \quad (5)$$

$\tilde{A}_D$ and $\tilde{B}_D$ multiplication:
$$\tilde{A}_D \times \tilde{B}_D = \left\{ \mu_{\tilde{A}_D}\mu_{\tilde{B}_D}, \left(v^2_{\tilde{A}_D} + v^2_{\tilde{B}_D} - v^2_{\tilde{A}_D}v^2_{\tilde{B}_D} \right)^{0.5}, \right.$$
$$\left. \times \left(\left(1 - v^2_{\tilde{B}_D} \right) \pi^2_{\tilde{A}_D} + \left(1 - v^2_{\tilde{A}_D} \right) \pi^2_{\tilde{B}_D} - \pi^2_{\tilde{A}_D}\pi^2_{\tilde{B}_D} \right)^{0.5} \right\} \quad (6)$$

$\tilde{A}_D$ with and a scalar $(\lambda > 0)$:
$$\lambda \times \tilde{A}_D = \left\{ \left(1 - \left(1 - \mu^2_{\tilde{A}_D} \right)^{\lambda} \right)^{0.5}, \right.$$
$$\left. \times v^{\lambda}_{\tilde{A}_D}, \left(\left(1 - \mu^2_{\tilde{A}_D} \right)^{\lambda} - \left(1 - \mu^2_{\tilde{A}_D} - \pi^2_{\tilde{A}_D} \right)^{\lambda} \right)^{0.5} \right\} \quad (7)$$

Power of $\tilde{A}_D$, with $\lambda > 0$ multiplication:
$$\tilde{A}^{\lambda}_D = \left\{ \mu^{\lambda}_{\tilde{A}_D}, \left(1 - \left(1 - v^2_{\tilde{A}_D} \right)^{\lambda} \right)^{0.5}, \right.$$
$$\left. \times \left(\left(1 - v^2_{\tilde{A}_D} \right)^{\lambda} - \left(1 - v^2_{\tilde{A}_D} - \pi^2_{\tilde{A}_D} \right)^{\lambda} \right)^{0.5} \right\} \quad (8)$$

B. MODEL OF THE SPHERICAL FUZZY ANALYTIC HIERARCHY PROCESS (SF-AHP)

Gundogdu and Kahraman [44] propose the SF-AHP approach, which is an extension of AHP using spherical fuzzy sets. The SF-AHP approach allows decision makers to reflect their hesitancy independently from membership and non-membership degrees, and therefore be able to generalize other fuzzy extensions of the AHP method.

In this study, SF-AHP is used to calculate the weights of the DC selection criterion. The SF-AHP approach consists of seven phases [44]:

Step 1: Create a hierarchical framework for the model.

A three-level hierarchical structure is built. The model's aim, based on a score index, is Level 1. The score index is determined by n criteria, which are represented in Level 2 of the structure. In Level 3 of the structure, a collection of m alternative A (m≥2) is specified.

Step 2: Create pairwise comparison matrices of the criteria based on linguistic phrases using spherical fuzzy judgement:

The score indices (SI) of each choice are calculated using Equation (9) and (10).

$$SI = \sqrt{\left| 100 * \left[\left(\mu_{\tilde{A}_D} - \pi_{\tilde{A}_D} \right)^2 - \left(v_{\tilde{A}_D} - \pi_{\tilde{A}_D} \right)^2 \right] \right|} \quad (9)$$

for AM, VH, HI, SM, and EI.

$$\frac{1}{SI} = \frac{1}{\sqrt{\left| 100 * \left[\left(\mu_{\tilde{A}_D} - \pi_{\tilde{A}_D} \right)^2 - \left(v_{\tilde{A}_D} - \pi_{\tilde{A}_D} \right)^2 \right] \right|}} \quad (10)$$

for SL, LI, VL, and AL.

Step 3: Examine each pairwise comparison matrix for consistency.

The classical consistency check is used, with a criterion of 10% for the Consistency Ratio (CR):

$$CR = \frac{CI}{RI} \quad (11)$$

The Consistency Index (CI) is computed as follows:

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (12)$$

where λ_{max} is the matrix's greatest eigenvalue and n is the number of criteria.

The Random Index (RI) is calculated using a set of criteria.

Step 4: Calculate the fuzzy weights of the criteria and options.

The following equation is used to calculate the weight of each choice in relation to each criterion:

$$
\begin{aligned}
SWM_w & \left(\tilde{A}_{D_{i1}}, \ldots, \tilde{A}_{D_{in}} \right) \\
& = w_1 \tilde{A}_{D_{i1}} + \ldots + w_n \tilde{A}_{D_{in}} \\
& = \langle \left[1 - \prod_{j=1}^{n} (1 - \mu^2_{\tilde{A}_{D_{ij}}})^{w_j} \right]^{0.5}, \prod_{n}^{j=1} V_{\tilde{A}_{D_{ij}}}^{w_j}, \\
& \times \left[\prod_{j=1}^{n} \left(1 - \mu^2_{\tilde{A}_{D_{ij}}} \right)^{w_j} \right. \\
& \left. - \prod_{j=1}^{n} \left(1 - \mu^2_{\tilde{A}_{D_{ij}}} - \pi^2_{\tilde{A}_{D_{ij}}} \right)^{w_j} \right]^{0.5} \rangle
\end{aligned}
\tag{13}
$$

where $w = 1/n$.

Step 5: Using hierarchical layer sequencing, obtain the global weights.

By aggregating the spherical weights at each level of the hierarchical structure, the ultimate ranking of the alternatives is computed. At this point, there are two viable options for carrying out the computation.

The first method is to defuzzify the criterion weights using the score function in Equation (14):

$$
S\left(\tilde{w}_j^D\right) = \sqrt{\left| \left| 100 * \left[\left(3\mu_{\tilde{A}_D} - \frac{\pi_{\tilde{A}_D}}{2} \right)^2 - \left(\frac{v_{\tilde{A}_D}}{2} - \pi_{\tilde{A}_D} \right)^2 \right] \right| \right|}
\tag{14}
$$

The criterion weights are then normalized using Equation (15) and spherical fuzzy multiplication is used in Equation (16):

$$
\bar{w}_j^D = \frac{D\left(\tilde{w}_j^D\right)}{\sum_{j=1}^{n} D\left(\tilde{w}_j^D\right)}
\tag{15}
$$

$$
\begin{aligned}
\tilde{A}_{D_{ij}} = \bar{w}_j^D * \tilde{A}_{D_i} & = \langle \left(1 - \left(1 - \mu^2_{\tilde{A}_{D_i}} \right)^{\bar{w}_j^D} \right)^{1/2}, \\
& \times v_{\tilde{A}_{D_i}}^{\bar{w}_j^D} \left((1 - \right. \\
& \left. \times \ \mu^2_{\tilde{A}_{D_i}} \right)^{\bar{w}_j^D} - \left(1 - \mu^2_{\tilde{A}_{D_i}} - \pi^2_{\tilde{A}_{D_i}} \right)^{\bar{w}_j^D} \right)^{1/2} \rangle
\end{aligned}
\tag{16}
$$

Equation (17) is used to determine the final ranking score ($\tilde{F}$) for each option A_i:

$$
\tilde{F} = \sum_{j=1}^{n} \tilde{A}_{D_{ij}} = \tilde{A}_{D_{i1}} + \tilde{A}_{D_{i2}} + \ldots + \tilde{A}_{D_{in}}
\tag{17}
$$

Another alternative is to proceed with the computation without defusing the criterion weights. The spherical fuzzy global weights are computed as follows:

$$
\prod_{j=1}^{n} \tilde{A}_{D_{ij}} = \tilde{A}_{D_{i1}} * \tilde{A}_{D_{i2}} * \ldots * \tilde{A}_{D_{in}}
\tag{18}
$$

The final ranking score ($\tilde{F}$) of each alternative is then computed using Equation (17).

C. THE ORDER OF PREFERENCE BY SIMILARITY TO THE IDEAL SOLUTION MODEL TECHNIQUE (TOPSIS)

TOPSIS is a multi-criteria decision analysis approach developed by Ching-Lai Hwang and Yoon in 1981 [45], with additional improvements by Yoon in 1987 [46] and Hwang, Lai, and Liu in 1993 [47]. The TOPSIS procedure is followed as follows:

Step 1: Create an evaluation matrix with m choices and n criteria, with the intersection of each alternative and criteria denoted by x_{fj}, yielding a matrix $(x_{fj})_{mxn}$.

Step 2: The matrix is then $(x_{fj})_{mxn}$ normalized to create the matrix.

Using the normalizing procedure, $R = (r_{ij})_{mxn}$

$$
r_{fj} = \frac{x_{fj}}{\sqrt{\sum_{k=1}^{m} x_{kj}^2}}, f = 1, 2, \ldots, m; j = 1, 2, \ldots, n
\tag{19}
$$

Step 3: Make a weighted normalized decision matrix.

$$
t_{fj} = r_{fj}.w_j, \ f = 1, 2, \ldots, m; \ j = 1, 2, \ldots, n
\tag{20}
$$

where $w_j = \frac{W_j}{\sum_{k=1}^{n} W_k}$, j =1,2, …,n so that $\sum_{f=1}^{n} w_j = 1$, and W_j denotes the indicator's initial weight v_j,j =1,2, …,n

Step 4: Determine the worst (A_w) and best (A_b) alternatives:

$$
\begin{aligned}
A_w & = \left\{ \begin{array}{l} \langle \max(t_{fj} \,|\, f = 1, 2, \ldots, m \,|\, j \in J_- \rangle, \\ \langle \min(t_{ij} \,|\, f = 1, 2, \ldots, m \,|\, j \in J_+ \rangle \end{array} \right\} \\
& = \{ t_{wj} | f = 1, 2, \ldots, n \}
\end{aligned}
\tag{21}
$$

$$
\begin{aligned}
A_b & = \left\{ \begin{array}{l} \langle \min(t_{fj} \,|\, f = 1, 2, \ldots, m \,|\, j \in J_- \rangle, \\ \langle \max(t_{ij} \,|\, f = 1, 2, \ldots, m \,|\, j \in J_+ \rangle \end{array} \right\} \\
& = \{ t_{wj} | f = 1, 2, \ldots, n \}
\end{aligned}
\tag{22}
$$

Step 5: Determine the L^2- distance between the goal alternative i and the worst-case scenario A_w.

$$
d_{fw} = \sqrt{\sum_{j=1}^{n} (t_{fj} - t_{wj})^2}, f = 1, 2, \ldots, m
\tag{23}
$$

And the distance between the preferred choice i and the worst-case scenario A_b.

$$
d_b = \sqrt{\sum_{j=1}^{n} (t_{fj} - t_{bj})^2}, f = 1, 2, \ldots, m
\tag{24}
$$

Step 6: Determine the degree of resemblance to the worst-case scenario:

$$
s_{iw} = \frac{d_{ib}}{(d_{iw} + d_{ib})}, i = 1\text{ma}2, \ldots, m
\tag{25}
$$

$s_{fw} = 1$ if and only if the alternative solution satisfies the best condition; and

$s_{fw} = 0$ if and only if the alternative solution has the worst condition.

Step 7: Sort the options based on s_{fw} ($f = 1, 2, \ldots, m$).

IV. CASE STUDY

According to data from the Electricity of Vietnam (EVN), as of October 31, 2021, the total installed capacity of renewable energy sources reached 20,644MW; in which, hydroelectricity accounts for 29.6; solar energy is 22.57%; wind energy is 5.16%; gas accounts for 10%; Oil is approximately 2% and biomass accounts for 0.28% of total power capacity.

That shows, the potential for renewable energy development in Vietnam is huge and the room for development is abundant. However, the implementation of renewable energy projects is currently facing new challenges such as: grid infrastructure and power system dispatching techniques due to the need to optimize new power sources into the system [48].

The author of this paper provides a Fuzzy Multicriteria Decision Making Model (FMCDM) that includes the SF-AHP and TOPSIS models for determining the best renewable energy resources (Solar energy (RE01); Solid Waste Energy (RE02); Biomass Energy (RE03); Wind Energy (RE04)) in a fuzzy environment. Main criteria and sub criteria are chosen based on Experts and literature evaluation, as shown in Fig. 2 the list of criteria affecting the decision process. In the first stage of this research, the author combines Spherical Fuzzy theory and AHP model for identifying the weight of all criteria, the results as shown in Tab. 3.
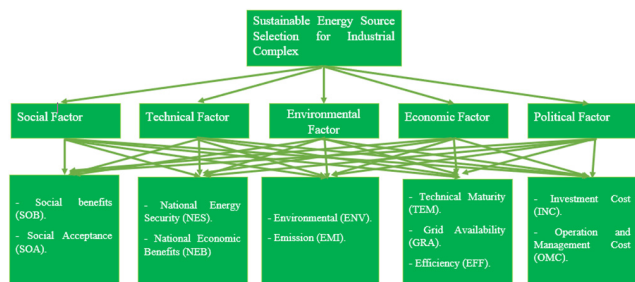

FIGURE 2. Criteria effecting to evaluation and selection processes.

TOPSIS is a MCDM model developed by Ching-Lai Hwang and Yoon. There are seven steps in the TOPSIS procedure. The author used TOPSIS model for ranking four potential renewable energy resources in second stage. normalized matrix and normalized weighted matrix are shown in Tab.4 and Tab. 5

In this research, the authors proposed a hybrid fuzzy MCDM model of the SF-AHP and TOPSIS concepts to develop a decision support system. A SFAHP was used to determine the weight of all criteria in the first stage, and the TOPSIS model was then used for ranking all potential renewable energy resources in the final stage. From the results in Tab. 6, the ranking list were RE01, RE03, RE02 and RE04, with scores of 0.6360, 0.5749, 0.5432 and 0.4475, respectively. Thus, RE01 (solar energy) is the optimal renewable energy resource.

TABLE 2. Linguistic importance measures [35].

Description	(μ, v, π)	Score Index
Absolutely more importance (AM)	(0.9, 0.1, 0.0)	9
Very high importance (VH)	(0.8, 0.2, 0.1)	7
High importance (HI)	(0.7, 0.3, 0.2)	5
Slightly more importance (SM)	(0.6, 0.4, 0.3)	3
Equally importance (EI)	(0.5, 0.4, 0.4)	1
Slightly lower importance (SL)	(0.4, 0.6, 0.3)	1/3
Low importance (LI)	(0.3, 0.7, 0.2)	1/5
Very low importance (VL)	(0.2, 0.8, 0.1)	1/7
Absolutely low importance (AL)	(0.1, 0.9, 0.0)	1/9

TABLE 3. The importance of the criteria.

Criteria	Spherical Fuzzy Weight			Crisp Weights
SOB	0.3736	0.6113	0.2768	0.0600
SOA	0.3662	0.6283	0.2760	0.0587
NES	0.4088	0.5990	0.2419	0.0675
NEB	0.4610	0.5454	0.2627	0.0765
ENV	0.5255	0.4919	0.2440	0.0889
ENI	0.5651	0.4578	0.2247	0.0968
TEM	0.6199	0.3888	0.2281	0.1067
GRA	0.6061	0.4041	0.2361	0.1039
EFF	0.6458	0.3535	0.2513	0.1107
INC	0.6585	0.3349	0.2629	0.1126
OMC	0.6820	0.3115	0.2395	0.1177

TABLE 4. Normalized matrix.

	RE01	RE02	RE03	RE04
SOB	0.4842	0.5447	0.4842	0.4842
SOA	0.4730	0.6082	0.3379	0.5406
NES	0.5275	0.5934	0.4616	0.3956
NEB	0.5560	0.4942	0.3707	0.5560
ENV	0.3956	0.5934	0.5275	0.4616
ENI	0.5449	0.6228	0.4671	0.3114
TEM	0.5431	0.4073	0.6110	0.4073
GRA	0.5482	0.4111	0.4796	0.5482
EFF	0.5431	0.3394	0.5431	0.5431
INC	0.4824	0.4221	0.5427	0.5427
OMC	0.4981	0.4358	0.4981	0.5603

V. SENSITIVITY ANALYSIS AND DISCUSION

In order to examine the outcome of the proposed method, a sensitivity analysis is peformed. There are many types of robust testing and sesitivity analysis, one of them

TABLE 5. Normalized weighted matrix.

	RE01	RE02	RE03	RE04
SOB	0.0291	0.0327	0.0291	0.0291
SOA	0.0278	0.0357	0.0198	0.0317
NES	0.0356	0.0401	0.0312	0.0267
NEB	0.0426	0.0378	0.0284	0.0426
ENV	0.0352	0.0528	0.0469	0.0410
ENI	0.0527	0.0603	0.0452	0.0301
TEM	0.0579	0.0435	0.0652	0.0435
GRA	0.0570	0.0427	0.0498	0.0570
EFF	0.0601	0.0376	0.0601	0.0601
INC	0.0543	0.0475	0.0611	0.0611
OMC	0.0586	0.0513	0.0586	0.0659

TABLE 6. Final ranking.

Alternatives	Si+	Si-	Ci	Ranking
RE01	**0.0248**	**0.0433**	**0.6360**	**1**
RE02	0.0373	0.0443	0.5432	3
RE03	0.0302	0.0407	0.5740	2
RE04	0.0440	0.0357	0.4475	4

TABLE 7. New criteria weights.

Criteria	New Crisp Weights
SOB	0.0637
NES	0.0717
NEB	0.0813
ENV	0.0944
ENI	0.1028
TEM	0.1134
GRA	0.1104
EFF	0.1176
INC	0.1196
OMC	0.1250

TABLE 8. New ranking.

Alternatives	Si+	Si-	Ci	Ranking
RE01	**0.0249**	**0.0452**	**0.6445**	**1**
RE02	0.0396	0.0440	0.5261	3
RE03	0.0273	0.0432	0.6130	2
RE04	0.0466	0.0357	0.4339	4

FIGURE 3. Alternatives' rankings in all scenarios.
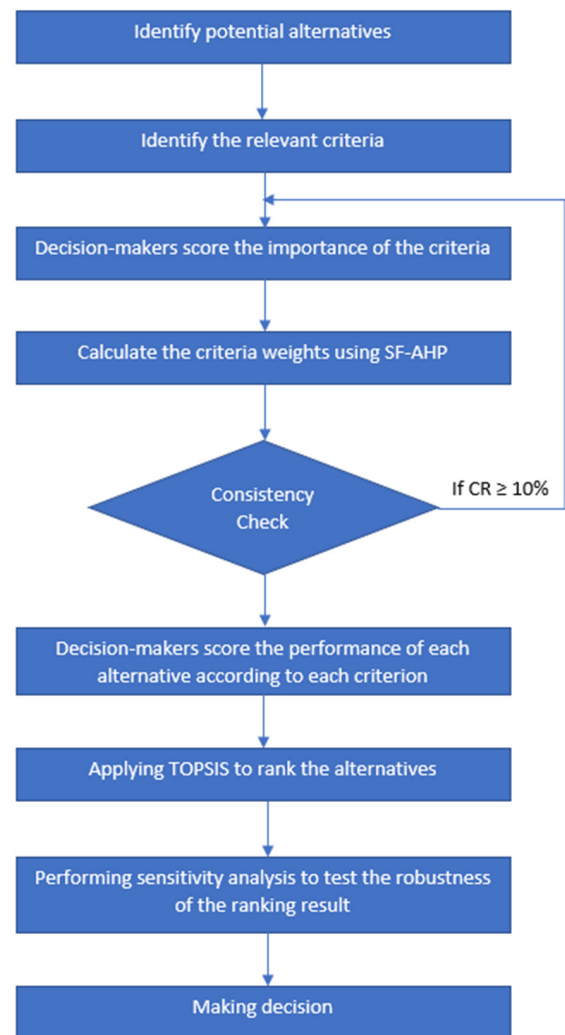
FIGURE 4. Proposed practical application process.

is calculating the final ranking of alternatives when the weight of a specific criteria is changed. In this case, the removal of the Social Acceptance criteria - SOA - and its impact to the final ranking will be performed. The sensitivity analysis follows the procedure introduced by Alinezhad and Amini [49].
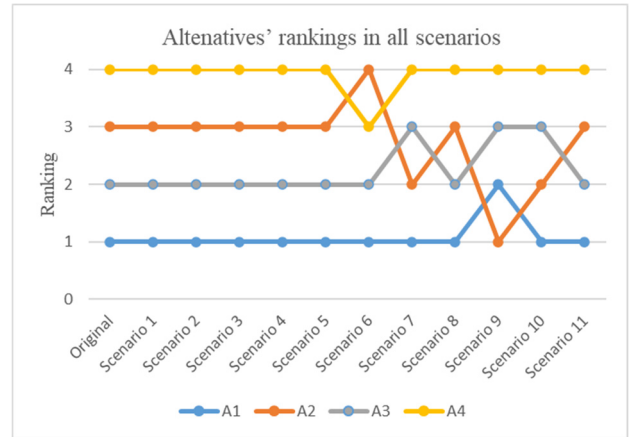
The new weights of the criteria after the removal of the SOA criteria are shown in Tab. 7:

TABLE 9. Criteria weights in all scenarios.

Criteria	Crisp Weights											
	Original	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Scenario 8	Scenario 9	Scenario 10	Scenario 11
SOB	0.0600	0	0.0637	0.0644	0.0650	0.0659	0.0665	0.0672	0.0670	0.0675	0.0677	0.0680
SOA	0.0587	0.0624	0	0.0629	0.0635	0.0644	0.0650	0.0657	0.0655	0.0660	0.0661	0.0665
NES	0.0675	0.0718	0.0717	0	0.0731	0.0741	0.0747	0.0756	0.0753	0.0759	0.0761	0.0765
NEB	0.0765	0.0814	0.0813	0.0821	0	0.0840	0.0847	0.0857	0.0854	0.0861	0.0862	0.0867
ENV	0.0889	0.0946	0.0944	0.0954	0.0963	0	0.0985	0.0995	0.0992	0.1000	0.1002	0.1008
ENI	0.0968	0.1030	0.1028	0.1038	0.1048	0.1062	0	0.1083	0.1080	0.1088	0.1091	0.1097
TEM	0.1067	0.1135	0.1134	0.1144	0.1155	0.1171	0.1181	0	0.1191	0.1200	0.1202	0.1209
GRA	0.1039	0.1106	0.1104	0.1114	0.1125	0.1141	0.1151	0.1163	0	0.1169	0.1171	0.1178
EFF	0.1107	0.1177	0.1176	0.1187	0.1198	0.1215	0.1225	0.1239	0.1235	0	0.1247	0.1254
INC	0.1126	0.1198	0.1196	0.1207	0.1219	0.1236	0.1246	0.1260	0.1256	0.1266	0	0.1276
OMC	0.1177	0.1252	0.1250	0.1262	0.1274	0.1291	0.1303	0.1317	0.1313	0.1323	0.1326	0

TABLE 10. Altenatives' performance scores in all scenarios.

Alterna tives	Performance Score (Ci)											
	Original	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Scenario 8	Scenario 9	Scenario 10	Scenario 11
A1	0.6445	0.6385	0.6445	0.6348	0.6227	0.7126	0.6100	0.6325	0.6226	0.5986	0.6421	0.6431
A2	0.5261	0.5423	0.5261	0.5314	0.5394	0.5219	0.4658	0.5940	0.5627	0.5988	0.5608	0.5288
A3	0.6130	0.5757	0.6130	0.5836	0.6041	0.5680	0.5909	0.5324	0.5771	0.5286	0.5594	0.5773
A4	0.4339	0.4483	0.4339	0.4594	0.4263	0.4532	0.5262	0.4821	0.4261	0.3856	0.4282	0.4620

Consequencially the performance score and ranking of the alternatives are shown in Tab. 8.

It can be seen that, while there are changes in the final performance scores of the alternatives (Ci), the final rankings are unchanged, with Solar Energy as the optimal renewable energy source in this case. This suggests that, in this case, the ranking of the alternatives is robust regrardless of the alternatives performance in the Social Acceptance criteria.

Similarly, 10 other scenarios where the final rankings of the alternatives were examined when the weight of each criterion is removed. The crisp weights of the criteria in all 11 scenarios are shown in Tab.9. The performance score of the alternatives are shown in Tab. 10 and their rankings are shown in Fig. 3.

From Tab.10 and Fig.3, we can see that the optimal altenative is A1 for most of the scenarios. In scenario 9, where A1 is the second most optimal altenative, its performance score is also very close to that of the optimal altenative A2 (0.5986 compared to 0.5988). This suggests that, while there are some changes in the ranking of other altenatives, A1 performs well across all scenarios.

VI. PRACTICAL APPLICATION PROCESS

For the practical application of the proposed method in sustainable energy source evaluation process for industrial

complexes, it is suggested that the decision-maker should adopt a seven-step process as shown in Fig4.

Step 1: The decision-makers related to the project should identify potential alternatives among available sustainable energy resources.

Step 2: The decision-makers must then identify the relevant evaluation criteria. This can be done by making a list of potential criteria by consulting industry experts and relevant literatures, then discuss to select relevant criteria to the project at hand. The list of criteria that was proposed in the case study session of this research can also be modified to suit the requirements of the decision-makers of different projects.

Step 3: After the relevant criteria are identified, the decision-makers must then score the importance of the criteria in relative to each other using a Linkert 9 scale.

Step 4: Then the data is used to calculate the weights of the criteria by using SF-AHP. This can be done simply by coding the calculation steps in Excel or Matlab.

Step 5: Perform the consistency check. If CR value is equal to or higher than 10%, step 3 and 4 must be performed again.

Step 6: The decision-makers then score the performance of each alternative according to each criterion using a Linkert 9 scale.

Step 7: Using the weights of each criterion calculated in step 4 and the individual performance score of each

alternative in step 6 to calculate the overall performance score of each alternative using TOPSIS.

Step 8: Performing sensitivity analysis as proposed to test the robustness of the result.

Step 9: Finally, the decision-makers can make the decision based on the result of the model.

The most significant contributions and successes in this study can be described as follows:

- The proposed model is the first renewable energy resources evaluation and selection process of industrial complexes development projects in Vietnam using expert interviews and literature reviews.
- Second, this is the first study to provide a case study on renewable energy resources evaluation and selection process of industrial complexes that utilizes a combination of SF-AHP and TOPSIS models.
- The results of this study can be a valuable guide in assessing and selecting renewable energy resources, not only for industrial complexes development projects in Vietnam but also the proposed approach can be applied to sustainable industrial complex around the world

VII. CONCLUSION

In recent years, the demand for electricity for production and socio-economic development has been increasing, which is a great challenge for the electricity industry in the context of domestic primary energy supply such as coal, stone, oil and gas… are exhausted not enough to meet the domestic demand, the development of renewable energy is a common trend of the world and Vietnam. The government also encourages the development of eco-industrial park and considers sustainable industrial complexes the cornerstone for the sustainability of Vietnam's industrial growth.

However, the selection of a suitable energy resource for each industrial complex project is not a simple task. Planners must take into consideration various quantitative and qualitative criteria when evaluating potential energy sources in order to select the optimal renewable energy option. In this work, the authors created a novel integrated Fuzzy Multicriteria Decision Making Model (FMCDM) for sustainable energy source selection that included a spherical fuzzy analytical hierarchy process (SF-AHP) and The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). This study is the first study to provide a case study on evaluating renewable energy resources by utilizing the combination of SF-AHP and TOPSIS models. The proposed approach can be applied to sustainable industrial complex around the world. Future research can extend the application of the Spherical Fuzzy number to develop new MCDM models to support solving decision making problems in other fields and industries. Comparision studies can also be done to evaluate the performance of Spherical fuzzy MCDM models in comparision with other extension of MCDM models

such as Intuitionistic fuzzy MCDM and Pythagorean fuzzy MCDM models.

REFERENCES

[1] K. Vietnam. (2022). *List of Vietnam Industrial Zone & Vietnam Industrial Park Map in 2021*. www.kizuna. Accessed: Jan. 28, 2022. [Online]. Available: https://www.kizuna.vn/en/news/difficulty-in-investing-in-vietnams-largest-industrial-zone-1020

[2] Vietnam's Ministry of Planning and Investment. (2022). *Báo Cáo Tình Hình Thành Lập Vá Phát Triên KCN, KKT 9 Tháng Năm 2021*. mpi.gov.vn. Accessed: Jan. 28, 2022. [Online]. Available: https://www.mpi.gov.vn/Pages/tinbai.aspx?idTin=51938&idcm=207

[3] S. Sacirovic, S. Ketin, and N. Vignjevic, "Eco-industrial zones in the context of sustainability development of urban areas," *Environ. Sci. Pollut. Res.*, vol. 26, no. 24, pp. 24346–24356, Aug. 2019.

[4] L. Chen, J. Olhager, and O. Tang, "Manufacturing facility location and sustainability: A literature review and research agenda," *Int. J. Prod. Econ.*, vol. 149, pp. 154–163, Mar. 2014.

[5] K. Das. (2022). *Renewables in Vietnam: Current Opportunities and Future Outlook*. Vietnam Briefing News. Accessed: Jan. 28, 2022. [Online]. Available: https://www.vietnam-briefing.com/news/vietnams-push-for-renewable-energy.html/

[6] United Nations Viet Nam. (2022). *Eco-Industrial Park—A Model for Sustainable Industrial Development of the Government of Viet Nam*. United Nations. Accessed: Jan. 28, 2022. [Online]. Available: https://vietnam.un.org/en/101985-eco-industrial-park-model-sustainable-industrial-development-government-viet-nam

[7] L. A. Zadeh, "Fuzzy sets," *Inf. Control*, vol. 8, no. 3, pp. 338–353, Jun. 1965.

[8] L. A. Zadeh, "The concept of a linguistic variable and its application to approximate reasoning-I," *Inf. Sci.*, vol. 8, no. 3, pp. 199–249, 1975.

[9] K. T. Atanassov, "Intuitionistic fuzzy sets," *Fuzzy Sets Syst.*, vol. 20, pp. 87–96, Aug. 1986.

[10] V. Torra, "Hesitant fuzzy sets," *Int. J. Intell. Syst.*, vol. 25, no. 6, pp. 529–539, 2010.

[11] R. Yager, "Properties and applications of Pythagorean fuzzy sets," in *Imprecision and Uncertainty in Information Representation and Processing*. New York, NY, USA: Springer, 2015, pp. 119–136.

[12] F. Smarandache, "Neutrosophic set—A generalization of the intuitionistic fuzzy set," in *Proc. IEEE Int. Conf. Granular Comput.*, 2006, pp. 1–29.

[13] F. K. Gündoğdu and C. Kahraman, "Spherical fuzzy sets and spherical fuzzy TOPSIS method," *J. Intell. Fuzzy Syst.*, vol. 36, no. 1, pp. 337–352, Feb. 2019.

[14] R. Y. K. Fung and F. Y. Wong, "Supplier environmental performance evaluation using AHP," in *Proc. Int. Symp. Analytic Hierarchy Process*, Aug. 2001, pp. 111–118.

[15] F. Dweiri, S. Kumar, S. A. Khan, and V. Jain, "Designing an integrated AHP based decision support system for supplier selection in automotive industry," *Expert Syst. Appl.*, vol. 62, pp. 273–283, Nov. 2016.

[16] C.-N. Wang, V. T. Nguyen, J.-C. Kao, C.-C. Chen, and V. T. Nguyen, "Multi-criteria decision-making methods in fuzzy decision problems: A case study in the frozen shrimp industry," *Symmetry*, vol. 13, no. 3, p. 370, Feb. 2021.

[17] K. Govindan, M. Shankar, and D. Kannan, "Supplier selection based on corporate social responsibility practices," *Int. J. Prod. Econ.*, vol. 200, pp. 353–379, Jun. 2018.

[18] P. T. Kieu, V. T. Nguyen, V. T. Nguyen, and T. P. Ho, "A spherical fuzzy analytic hierarchy process (SF-AHP) and combined compromise solution (CoCoSo) algorithm in distribution center location selection: A case study in agricultural supply chain," *Axioms*, vol. 10, no. 2, p. 53, Apr. 2021.

[19] S. Tadiè, M. Krstiè, V. Roso, and N. Brnjac, "Dry port terminal location selection by applying the hybrid grey MCDM model," *Sustainability*, vol. 12, no. 17, p. 6983, Aug. 2020.

[20] A. Budak, I. Kaya, A. Karaşan, and M. Erdoğan, "Real-time location systems selection by using a fuzzy MCDM approach: An application in humanitarian relief logistics," *Appl. Soft Comput.*, vol. 92, Jul. 2020, Art. no. 106322.

[21] A. Karasan, I. Kaya, and M. Erdogan, "Location selection of electric vehicles charging stations by using a fuzzy MCDM method: A case study in Turkey," *Neural Comput. Appl.*, vol. 32, no. 9, pp. 4553–4574, 2020.

[22] C.-N. Wang, H.-P. Fu, H.-P. Hsu, V. Thanh Nguyen, V. Tinh Nguyen, and A. Saleh Ahmar, "A model for selecting a biomass furnace supplier based on qualitative and quantitative factors," *Comput., Mater. Continua*, vol. 69, no. 2, pp. 2339–2353, 2021.

[23] F. Chien, C.-N. Wang, V. T. Nguyen, V. T. Nguyen, and K. Y. Chau, "An evaluation model of quantitative and qualitative fuzzy multi-criteria decision-making approach for hydroelectric plant location selection," *Energies*, vol. 13, no. 11, p. 2783, Jun. 2020.

[24] G. Büyüközkan and E. Mukul, "Evaluation of smart health technologies with hesitant fuzzy linguistic MCDM methods," *J. Intell. Fuzzy Syst.*, vol. 39, no. 5, pp. 6363–6375, Nov. 2020.

[25] K. H. Doerr, W. R. Gates, and J. E. Mutty, "A hybrid approach to the valuation of RFID/MEMS technology applied to ordnance inventory," *Int. J. Prod. Econ.*, vol. 103, no. 2, pp. 726–741, Oct. 2006.

[26] F. S. Abdulgader, R. Eid, and B. D. Rouyendegh, "Development of decision support model for selecting a maintenance plan using a fuzzy MCDM approach: A theoretical framework," *Appl. Comput. Intell. Soft Comput.*, vol. 2018, pp. 1–14, Nov. 2018.

[27] A. Pınar, R. B. Daneshvar, and Y. S. Özdemir, "Q-rung orthopair fuzzy TOPSIS method for green supplier selection problem," *Sustainability*, vol. 13, no. 2, p. 985, Jan. 2021.

[28] B. D. Rouyendegh, "Developing an integrated AHP and intuitionistic fuzzy TOPSIS methodology," *Tech. Gazette*, vol. 21, no. 6, pp. 1313–1319, 2014.

[29] C. Erdin and G. Ozkaya, "Turkey's 2023 energy strategies and investment opportunities for renewable energy sources: Site selection based on ELECTRE," *Sustainability*, vol. 11, no. 7, p. 2136, Apr. 2019.

[30] H. U. Abdelhady, Y. E. Imam, Z. Shawwash, and A. Ghanem, "Parallelized bi-level optimization model with continuous search domain for selection of run-of-river hydropower projects," *Renew. Energy*, vol. 167, pp. 116–131, Apr. 2021.

[31] P. Adhikary, P. K. R. Roy, and A. Mazumdar, "Small hydropower site selection using spatial-fuzzy expert system: A case study," *Reason Tech. J.*, vol. 13, p. 49, Jul. 2016.

[32] S. Suryadimal, A. Ambiyar, G. Ganefri, F. Rizal, and N. Jalinu, "Selection criteria of feasibility assessment on mini hydro power plant in batang sumani river solok west sumatera," *J. Phys., Conf. Ser.*, vol. 1469, no. 1, Feb. 2020, Art. no. 012177.

[33] B. Karatop, B. Taşkan, E. Adar, and C. Kubat, "Decision analysis related to the renewable energy investments in Turkey based on a fuzzy AHP-EDAS-Fuzzy FMEA approach," *Comput. Ind. Eng.*, vol. 151, Jan. 2021, Art. no. 106958.

[34] V. T. Nguyen, N. H. Hai, and N. T. K. Lan, "Spherical fuzzy multicriteria decision-making model for wind turbine supplier selection in a renewable energy project," *Energies*, vol. 15, no. 3, p. 713, Jan. 2022.

[35] K. Kokkinos and V. Karayannis, "Supportiveness of low-carbon energy technology policy using fuzzy multicriteria decision-making methodologies," *Mathematics*, vol. 8, no. 7, p. 1178, Jul. 2020.

[36] C. N. Wang, N. A. A. Nguyen and T. T. Dang, "Offshore wind power station (OWPS) site selection using a two-stage MCDM-based spherical fuzzy set approach," *Sci. Rep.*, vol. 12, no. 1, pp. 1–21, 2022.

[37] Y. A. Solangi, C. Longsheng, and S. A. A. Shah, "Assessing and overcoming the renewable energy barriers for sustainable development in Pakistan: An integrated AHP and fuzzy TOPSIS approach," *Renew. Energy*, vol. 173, pp. 209–222, Aug. 2021.

[38] S. Sindhu, V. Nehra, and S. Luthra, "Investigation of feasibility study of solar farms deployment using hybrid AHP-TOPSIS analysis: Case study of India," *Renew. Sustain. Energy Rev.*, vol. 73, pp. 496–511, Jun. 2017.

[39] I. Sharaf, *Spherical Fuzzy VIKOR With SWAM and SWGM Operators For MCDM* Decision Making with Spherical Fuzzy Sets. New York, NY, USA: Springer, 2020, pp. 217–240.

[40] I. Otay and S. Atik, "Multi-criteria oil station location evaluation using spherical AHP&WASPAS: A real-life case study," in *Proc. Adv. Intell. Syst. Comput.*, 2020, pp. 591–598.

[41] S. Gül, "Spherical fuzzy extension of DEMATEL (SF-DEMATEL)," *Int. J. Intell. Syst.*, vol. 35, no. 9, pp. 1329–1353, Sep. 2020.

[42] R. R. Yager, "Pythagorean fuzzy subsets," in *Proc. Joint IFSA World Congr. NAFIPS Annu. Meeting (IFSA/NAFIPS)*, Jun. 2013, pp. 57–61.

[43] F. Smarandache, *A unifying Field In Logics Neutrosophy: Neutrosophic Probability, Set and Logic*. Rehboth: American Research Press.

[44] F. K. Gündoğdu and C. Kahraman, "A novel spherical fuzzy analytic hierarchy process and its renewable energy application," *Soft Comput.*, vol. 24, no. 6, pp. 4607–4621, Mar. 2020.

[45] C. Hwang and K. Yoon, *Multiple Attribute Decision Making*. New York, NY, USA: Springer, 1981.

[46] K. Yoon, "A reconciliation among discrete compromise solutions," *J. Oper. Res. Soc.*, vol. 38, no. 3, pp. 277–286, Mar. 1987.

[47] C.-L. Hwang, Y.-J. Lai, and T.-Y. Liu, "A new approach for multiple objective decision making," *Comput. Oper. Res.*, vol. 20, no. 8, pp. 889–899, 1993.

[48] N. Quynh. (2022). *Co Chê Thu Hút Dâu Tu Phát Triên Bên Vũng Năng Luong Tái Tao Tai Viêt Nam*. www. https://moit.gov.vn/. Accessed: Dec. 28, 2021. [Online]. Available: https://moit.gov.vn/tin-tuc/phat-trien-nang-luong/co-che-thu-hut-dau-tu-phat-trien-ben-vung-nang-luong-tai-tao-tai-viet-nam.html

[49] A. Alinezhad and A. Amini, "Sensitivity analysis of TOPSIS technique: The results of change in the weight of one attribute on the final ranking of alternatives," *J. Optim. Ind. Eng.*, vol. 4, no. 7, pp. 23–28, 2011.

NGUYEN VAN THANH was born in Can Tho City, Vietnam, in 1989. He received the B.S. degree in industrial management from Can Tho University, the M.S. degree in industrial system engineering from the Ho Chi Minh University of Technology and Vietnam National University, and the Ph.D. degree in industrial engineering and management from the National Kaohsiung University of Science and Technology, Taiwan, in 2019.

From 2013 to 2019, he was the Deputy Head of the Industrial Systems Engineering Department, Can Tho University of Technology. Since 2019, he has been working with the Faculty of Technology, Hong Bang International University, as the Vice Dean. Since 2020, he has been the Head of Logistics and Supply Chain Management, Van Lang University, Ho Chi Minh City, Vietnam. He is the author of two books and more than 50 research articles. His research interests include operation research, logistics and supply chain management, and data science.