



Choice Optimal Fuel Alternative in Thermal Power Station Using Neutrosophic Set and MCDM Methodology

Edmundo Jalón Arias¹, Luis Freire Lescano¹, Giovanni Pineda Silva², Maha Ibrahim³

¹Docente de la carrera de Software de la Universidad Regional Autónoma de los Andes (UNIANDES), Ecuador

²Docente de la carrera de Automotriz de la Universidad Regional Autónoma de los Andes (UNIANDES) Sede Santo Domingo, Ecuador

³Tashkent state university of Economics, Tashkent, Uzbekistan

Emails: uq.sistemas@uniandes.edu.ec; ciad@uniandes.edu.ec; ua.giovannypineda@uniandes.edu.ec; M.abdelazim@tsue.uz

Abstract

In a power plant, the fuel choice directly impacts the efficiency, cost, and ecological impact of generating electricity. For power plants to produce electricity effectively and affordably to fulfill the needs of consumers in homes, companies, and communities, they need a fuel supply that is constant, dependable, and inexpensive. In this study, we used the concept of multi-criteria decision-making (MCDM) to deal with the various criteria of fuel alternatives. We used the EDAS method as an MCDM methodology to rank the fuel alternatives and select the best one. The EDAS method is employed with the interval-valued neutrosophic sets (IVNSs) to deal with the uncertainty information in the evaluation process. We compute the weights of the criteria of thermodynamic parameters. We used ten thermodynamic parameters such as temperature, mass, energy, etc. Then, the principal results show that temperature is the best criterion, and the work interaction is the worst criterion in all criteria. The EDAS method ranked twenty alternatives. The results show that alternative 20 are the best and alternative 14 is the worst of all alternatives. We employed the sensitivity analysis to show the rank of alternatives under ten cases. The results show the 20 alternative is the best in all cases. The results are stable.

Keywords: Interval Valued Neutrosophic Sets; MCDM, EDAS Method; Thermal Power Station; Fuel Power; Energy.

1. Background

Choosing the right fuel for a power plant is crucial since it affects the facility's output, expenses, and ecological footprint. To successfully produce electricity and fulfill the energy needs of companies, organizations, and communities, power plants need a constant, dependable, and cost-effective fuel supply. The choice of fuel relies on a multiplicity of criteria, including availability, cost, energy content, environmental concerns, and technical compatibility with the power plant's equipment and infrastructure[1], [2].

Power plant operators and energy planners must make decisions on which fuel will be most efficient, cost-effective, and environmentally friendly in this setting. When making a decision, it's important to weigh the long-term and short-term consequences of the available fuel alternatives. The ideal fuel choice for a power plant is determined by a number of factors, including the fuel's availability, price volatility, energy efficiency, emissions profile, and regulatory compliance[3], [4].

Furthermore, there are other factors than cost to consider while choosing a fuel. Greenhouse gas emissions, air quality, and our total carbon footprint are just a few of the environmental issues that have come to the forefront in recent years. In order to lessen their negative effects on the environment and aid global efforts to combat climate change, power plants are coming under growing pressure to switch to cleaner and more sustainable fuel sources[5], [6].

Coal, natural gas, oil, nuclear, biomass, and renewable energy sources including solar, wind, hydro, and geothermal must all be considered by power plant operators in this intricate decision-making process[7]–[9]. In terms of accessibility, cost, energy density, emissions, and operational factors, each fuel source has its own pros and disadvantages[10], [11].

A power plant's fuel choice should strike a good balance between cost, environmental impact, and plant operations. It requires an in-depth familiarity with the energy industry, new technologies, and relevant regulations. Power plants may help make the energy industry more resilient, efficient, and ecologically responsible by making well-informed choices and adopting sustainable fuel sources[12], [13].

Thermodynamic perspectives might be used in the analysis of this study. The thermodynamics regulate the herbal phenomena and are also valid for synthetic systems[14], [15].

The literature survey reveals that researchers in various domains have utilized qualitative and quantitative frameworks for decision-making[16], [17].

Decision analysis and management science have tremendously aided in fuel selection. When compared to other decision-making techniques, multi-criteria decision-making (MCDM) approaches provide superior models for aiding in the solution of complex, interconnected choice issues. Multiple criterion approaches, which evaluate and rank options based on a number of factors, serve as a direct defining characteristic. It details a quantitative technique that may help DMs be more strategic in their decision-making by systematically weighing relevant factors[18], [19].

Using a fuzzy set (FS) technique is the cornerstone notion for addressing doubts during choice-making. There have been several uses for the traditional fuzzy decision-making models. Numerological intervals, intuitionistic models, the rough set (RS), and the FS are often used in this context[20]–[24]. The most current technique in this area, generally known as neutrosophic set (NS) notions, developed and championed by Kandasamy and Smarandache, is employed in the present work. With the use of numerical examples, Kandasamy and Smarandache explained the mathematical and philosophical underpinnings of neutrosophic algebraic buildings, neutrosophic spaces, and neutrosophic matrices[25], [26].

Mondal and Pramanik created a model of collaborative decision-making in the context of higher education faculty hiring from a neutrosophic perspective. ahin and Liu explored several fundamental aspects and characteristics of single-valued neutrosophic hesitant fuzzy sets (SVNHFS) and outlined their correlation and correlation coefficient[27], [28]. Using neutrosophic fuzzy notions, Vafadarnikjoo et al. investigated key motivating characteristics of a refurbished bike based on the views of customers and experts[29], [30].

NSs factor in the uncertainty and inconsistency of individual aspects when they work to find solutions to real-time challenges. In contrast with FSs and intuitionistic FSs (IFSs), NSs indicate incompleteness and inconsistency of an element to set, making it more suited for handling complicated issues[31]–[33].

The main contributions of this study are:

We analyze the thermodynamics parameters by the average method to show the weights of these parameters.

We conducted a sensitivity analysis to show the stability of the results and the rank of alternatives under different cases.

We employed the interval-valued neutrosophic sets with the EDAS method to overcome the uncertainty information.

The MCDM methodology to rank the alternatives by employing the EDAS method.

There are ten criteria and 20 alternatives are used in this paper.

2. Interval Valued Neutrosophic Sets

In this section, we introduce some operations on the interval-valued neutrosophic numbers (IVNNs) as:

The IVNNs can be defined as:

$$x = [T_x^L, T_x^U], [I_x^L, I_x^U], [F_x^L, F_x^U]$$

Where T refers to the truth values, I refers to the indeterminacy values and F refers to the falsity values.

There are some operations on IVNNs as:

$$\rho x = \left\{ \begin{aligned} & [1 - (1 - T_x^L(A))^\rho, 1 - (1 - T_x^U(A))^\rho] \\ & [((I_x^L(A))^\rho, ((I_x^U(A))^\rho))] \\ & [((F_x^L(A))^\rho, ((F_x^U(A))^\rho))] \end{aligned} \right\} \tag{1}$$

$$x^\rho = \left\{ \begin{aligned} & [(T_x^L(A))^\rho], \\ & [1 - (1 - I_x^L(A))^\rho, 1 - (1 - I_x^U(A))^\rho] \\ & [1 - (1 - F_x^L(A))^\rho, 1 - (1 - F_x^U(A))^\rho] \end{aligned} \right\} \tag{2}$$

We let two IVNNs as $x = [T_x^L(A), T_x^U(A)], [I_x^L(A), I_x^U(A)], [F_x^L(A), F_x^U(A)]$ and $y = [T_y^L(A), T_y^U(A)], [I_y^L(A), I_y^U(A)], [F_y^L(A), F_y^U(A)]$

$$x + y = \left\{ \begin{aligned} & [T_x^L(A) + T_y^L(A) - T_x^L(A) \cdot T_y^L(A), T_x^U(A) + T_y^U(A) - T_x^U(A) \cdot T_y^U(A)], \\ & [T_x^L(A) \cdot I_y^L(x), I_x^L(A) \cdot I_y^U(A)], \\ & [F_x^L(A) \cdot F_y^L(x), F_x^L(A) \cdot F_y^U(A)] \end{aligned} \right\} \tag{3}$$

$$x - y = \left\{ \begin{aligned} & [T_x^L(A) - T_y^L(A), T_x^U(A) - T_y^U(A)], \\ & [\max(I_x^L(x) \cdot I_y^L(x)), \max(I_x^U(A) \cdot I_y^U(A))], \\ & [F_x^L(A) - F_y^L(A), F_x^U(A) - F_y^U(A)] \end{aligned} \right\} \tag{4}$$

$$x \cdot y = \left\{ \begin{aligned} & [T_x^L(A) \cdot T_y^L(A), T_x^U(A) \cdot T_y^U(A)], \\ & [T_x^L(A) + I_y^L(A) - T_x^L(A) \cdot I_y^L(A), I_x^U(A) + I_y^U(A) - I_x^U(A) \cdot I_y^U(A)], \\ & [F_x^L(A) + F_y^L(A) - F_x^L(A) \cdot F_y^L(A), F_x^U(A) + F_y^U(A) - F_x^U(A) \cdot F_y^U(A)] \end{aligned} \right\} \tag{5}$$

3. EDAS Method

In this section, we introduce the EDAS method as an MCD method and show the steps of the EDAS method under the interval-valued neutrosophic sets.

The EDAS method, created by Ghorabae et al. (2015), is intended to be faster and less labor-intensive than other methods of assessing alternatives in terms of their distance from a mean solution. The EDAS method, backed by experimental data, was put to use in the building industry to pinpoint the best fuel for a power plant. By contrasting EDAS with other methodologies, we were able to prove its worth as an MCDM strategy. Using both beneficial and detrimental distances to evaluate helpful and harmful criteria, the approach ranks alternatives based on how far they deviate from the mean answer for each factor. The steps of the EDAS method as shown in Figure 1 and are organized as follows:

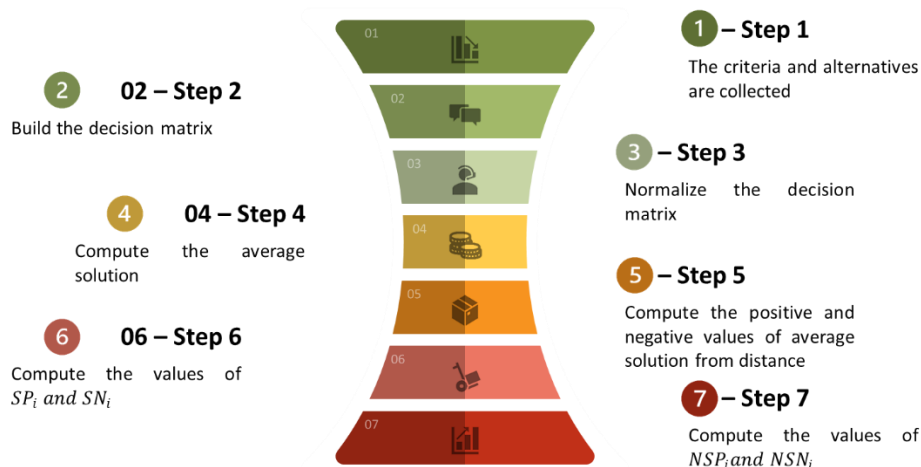


Figure 10: The Steps of the interval-valued neutrosophic EDAS method.

3.1 The criteria and alternatives are collected

We let the experts and decision-makers collect the criteria based on their expertise in the energy and power station fuel. These criteria are gathered from previous related work of power fuel in power stations.

3.2 Build the decision matrix

After the experts and decision-makers collected the criteria and alternatives, they used the linguistic terms of interval-valued neutrosophic sets to evaluate the criteria and alternatives to build the decision matrix. Then we replace the linguistic terms with related interval-valued neutrosophic numbers. Then we apply the score function to obtain the crisp values in the decision matrix.

3.3 Normalize the decision matrix

The decision matrix between criteria and alternatives by the crisp values are normalized to build the normalized decision matrix.

$$N_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^A x_{ij}^2}} \tag{6}$$

Where x_{ij} refers to the value in the decision matrix and $i = 1, 2, \dots, m(\text{alternatives})$ and $j = 1, 2, \dots, n(\text{criteria})$

3.4 Compute the average solution

$$AV_j = \frac{\sum_{i=1}^c x_{ij}}{n} \tag{7}$$

3.5 Compute the positive and negative values of the average solution from a distance

If j is positive

$$PDA_{ij} = \frac{\max(0, (x_{ij} - AV_j))}{AV_j} \tag{8}$$

$$NDA_{ij} = \frac{\max(0, (AV_j - x_{ij}))}{AV_j} \tag{9}$$

If j is negative

$$PDA_{ij} = \frac{\max(0, (AV_j - x_{ij}))}{AV_j} \quad (10)$$

$$NDA_{ij} = \frac{\max(0, (x_{ij} - AV_j))}{AV_j} \quad (11)$$

3.6 Compute the values of SP_i and SN_i

$$SP_i = \sum_{j=1}^A W_j PDA_{ij} \quad (12)$$

$$SN_i = \sum_{j=1}^A W_j NDA_{ij} \quad (13)$$

3.7 Compute the values of NSP_i and NSN_i

$$NSP_i = \frac{SP_i}{\max(SP_i)} \quad (14)$$

$$NSN_i = 1 - \frac{SN_i}{\max(SN_i)} \quad (15)$$

3.8 Compute the AS_i

$$AS_i = \alpha (NSP_i + NSN_i) \quad (16)$$

4. Discussion

In this section, we offer the results of the interval-valued neutrosophic EDAS method. We show the weights of criteria and rank and select the best power station based on a set of criteria and alternatives.

4.1 We collect the criteria and alternatives from previous studies to rank the power stations and evaluate the weights of power weights. We collected the ten criteria and twenty alternatives. We collect the criteria of this paper by the thermodynamic parameters. Thermodynamic parameters are a variable state the thermodynamic behavior. The thermodynamic parameters offer some benefits to the systems such as work interaction, heat transfer, and energy. The ten thermodynamic parameters used in this paper are organized as follows:

4.1.1 Gibbs free energy: This parameter refers to the combined enthalpy and entropy to compute the amount of energy in the system.

4.1.2 Heat: This parameter refers to the transfer of energy between a system.

4.1.3 Energy: This parameter is the capacity to do work in the system.

4.1.4 Mass or Volume: This parameter refers to the amount of space occupied by the system.

4.1.5 Temperature: This parameter measures the mean of kinetic energy of practices in systems.

4.1.6 Entropy: This parameter refers to the disorder of a system.

4.1.7 Pressure: This parameter refers to the force exerted per unit area by gas.

4.1.8 Internal Energy: This parameter refers to the sum of the microscopic energy of particles within the system.

4.1.9 Enthalpy: This parameter refers to the total heat content of a system at constant pressure.

4.1.10 Work: This parameter refers to the transfer energy of outcomes in a change in state in the system.

4.2 Build the decision matrix

We used the ten criteria and twenty alternatives to build the decision matrix between the criteria and alternatives. We used the interval-valued neutrosophic numbers to build the decision matrix.

4.3 We used Eq. (6) to build the normalized decision matrix between criteria and alternatives.

4.4 Eq. (7) is used to compute the average solution from the normalized decision matrix.

4.5 Eqs. (8 and 9) are used to compute the values of positive and negative average solutions from the distance as shown in Tables 1 and 2.

Table 1: The positive average solutions from the distance.

	TPC ₁	TPC ₂	TPC ₃	TPC ₄	TPC ₅	TPC ₆	TPC ₇	TPC ₈	TPC ₉	TPC ₁₀
TPA ₁	0.61641 6	0.34707 4	0.98647 7	0.30158 6	0	0	0	0	0	0.52558 3
TPA ₂	0	0.61380 8	0.94913 1	0	0	0.52662 2	0	0.53761 3	0.55862 9	0.53821
TPA ₃	0.14506 3	0	0.97221 5	0	0	0	0	0	0.59358 7	0.33437 4
TPA ₄	0.40024 4	0.13925	0.96661 6	0.00442 9	0	0	0	0	0.55914 5	0.05062 5
TPA ₅	0	0	0.98753 4	0	0.04520 7	0.52662 2	0.53164 8	0	0.59358 7	0.05657 8
TPA ₆	0.14506 3	0.13925	0.98646 1	0.55331 8	0	0	0.49136 2	0	0	0.73843 9
TPA ₇	0.14506 3	0.34707 4	0.94913 1	0.51489 6	0.57161 4	0	0	0	0.09418 1	0
TPA ₈	0	0	0.97221 5	0	0.53476 6	0	0	0	0.78818 3	0
TPA ₉	0.14506 3	0.13925	0.96661 6	0.00442 9	0	0.52662 2	0	0	0.10106 9	0.53821
TPA ₁₀	0.40024 4	0	0.98753 4	0	0.57161 4	0.48590 4	0.53164 8	0	0	0.34700 1
TPA ₁₁	0	0.13777 7	0.98646 1	0.55331 8	0.53476 6	0.25984 6	0.49136 2	0.53761 3	0	0
TPA ₁₂	0	0	0.96661 6	0.51489 6	0.34289 9	0	0	0.49784	0	0.05116 7
TPA ₁₃	0.14506 3	0.13925	0.98050 8	0	0	0	0	0	0.09418 1	0.23696 5
TPA ₁₄	0	0	0.94913 1	0.00442 9	0.04520 7	0	0.53164 8	0	0	0.05657 8
TPA ₁₅	0	0	0.97221 5	0	0	0.52662 2	0.49136 2	0	0.28533 3	0
TPA ₁₆	0.32547 7	0.13925	0.96661 6	0.55331 8	0.57161 4	0.48590 4	0	0.53761 3	0	0
TPA ₁₇	0.14506 3	0	0.98753 4	0.51489 6	0.53476 6	0	0	0.49784	0	0
TPA ₁₈	0	0.13925	0.98646 1	0.55161 4	0.33019 3	0.52662 2	0	0.27703 1	0	0.05116 7
TPA ₁₉	0.14506 3	0	0.97221 5	0	0	0.48590 4	0.26770 5	0	0	0
TPA ₂₀	0	0.13925	0	0.00442 9	0	0	0	0.48471 3	0	0

Table 2. The negative average solutions from the distance.

	TPC ₁	TPC ₂	TPC ₃	TPC ₄	TPC ₅	TPC ₆	TPC ₇	TPC ₈	TPC ₉	TPC ₁₀
--	------------------	------------------	------------------	------------------	------------------	------------------	------------------	------------------	------------------	-------------------

TPA ₁	0	0	0	0	0.55417	0.39405	0.25423	0.45965	0.66698	0
						7		4	2	
TPA ₂	0.02722	0	0	0.19619	0.74258	0	0.91111	0	0	0
	5			9	7		2			
TPA ₃	0	0.04566	0	0.82269	0.14720	0.05507	0.04386	0.03057	0	0
		4			3		8	4		
TPA ₄	0	0	0	0	0.74803	0.34190	0.25423	0.23825	0	0
					3	5		7		
TPA ₅	0.02885	0.04566	0	0.19619	0	0	0	0.03057	0	0
		4		9				4		
TPA ₆	0	0	0	0	0.14720	0.93162	0	0.23825	0.65665	0
					3	1		7		
TPA ₇	0	0	0	0	0	0.05507	0.91111	0.03057	0	0.14004
							2	4		3
TPA ₈	0.56521	0.52513	0	0.82269	0	0.26768	0.04386	0.88677	0	0.73712
	7	1				9	8	4		3
TPA ₉	0	0	0	0	0.14720	0	0.25423	0.03057	0	0
					3			4		
TPA ₁₀	0	0.04566	0	0.19619	0	0	0	0.23825	0.08836	0
		4		9				7		
TPA ₁₁	0.56034	0	0	0	0	0	0	0	0.08836	0.73712
	1									3
TPA ₁₂	0.39130	0.04566	0	0	0	0.93162	0.04386	0	0.65837	0
	4	4				1	8		2	
TPA ₁₃	0	0	0	0.82269	0.74803	0.05507	0.25423	0.88677	0	0
					3			4		
TPA ₁₄	0.56521	0.57586	0	0	0	0.26768	0	0.03057	0.47410	0
	7					9		4	8	
TPA ₁₅	0.02722	0.03420	0	0.19619	0.14720	0	0	0.23825	0	0.14004
	5	9		9	3			7		3
TPA ₁₆	0	0	0	0	0	0	0.25423	0	0.09352	0.14004
									7	3
TPA ₁₇	0	0.57586	0	0	0	0.26768	0.04386	0	0.65837	0.73712
						9	8		2	3
TPA ₁₈	0.56521	0	0	0	0	0	0.02402	0	0.09438	0
	7						3		8	
TPA ₁₉	0	0.52676	0	0.82269	0.55380	0	0	0.03116	0.10041	0.35650
		8			7			2	5	7
TPA ₂₀	0.02722	0	18.4916	0	0.14720	0.78318	0.04386	0	0.08836	0.53689
	5		9		3	9	8			4

4.6 Then compute the values of SP_i and SN_i by using Eqs. (12) and 13. Before that we compute the weights of criteria by the average method as shown in Figure 2. We show the temperature criterion is the best and the work criterion is the worst.

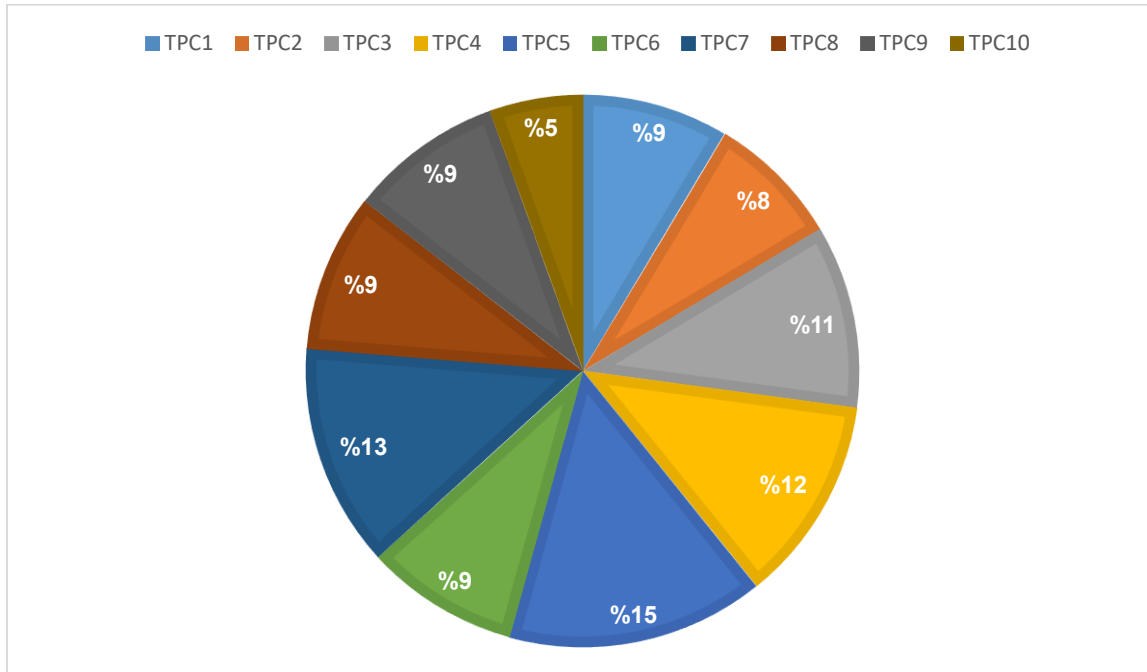


Figure 2: The ten weights of thermodynamic parameters.

4.7 Then compute the values of NSP_i and NSN_i by using Eqs. (14 and 15).

4.8 Then compute the AS_i by using Eq. (16) as shown in Figure 3. Alternative 20 is the best fuel and alternative 14 is the worst.

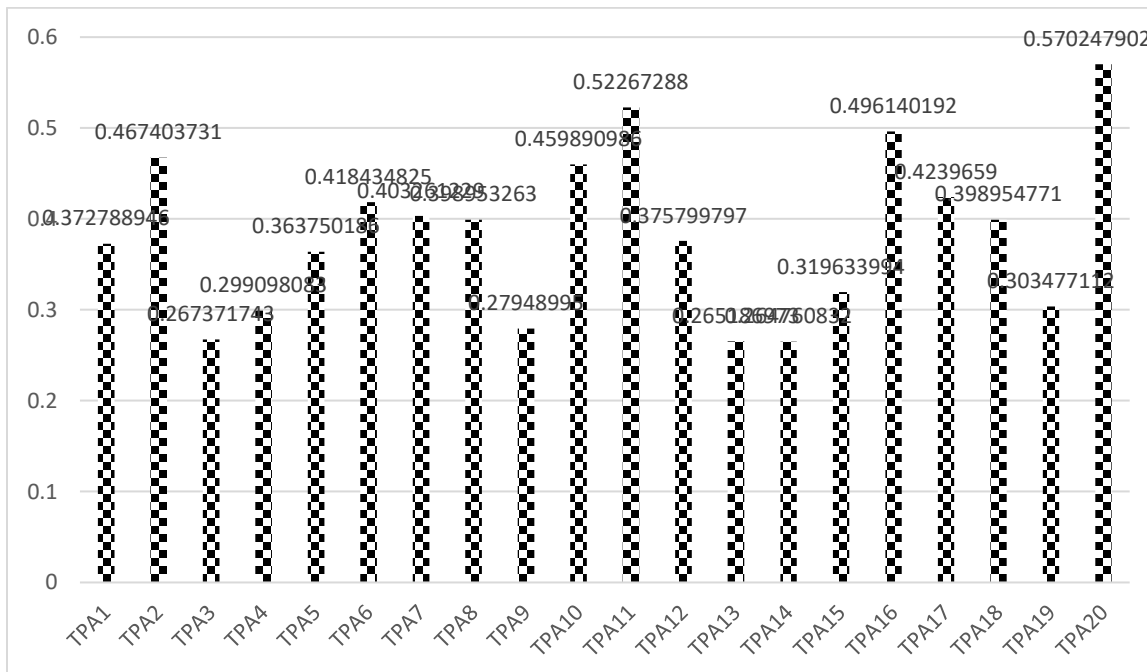


Figure 3: The value of AS_i for 20 alternatives.

4.9 Sensitivity analysis

We change the value of α between 0 and 1 then rank the alternatives to show the stability of the outcome of the proposed method. The α we put with 0.5 weight then rank the alternative. The results show that alternative 20 is the best and alternative 14 is the worst.

Then we put the α with values between 0 and 1. The rank of alternative are shown in Figure 4. We show that all cases are identical Alternative 20 is the highest score alternative 14 is the worst and all ranks are the same as $\alpha = 0.5$. This indicates the results are stable and the proposed model is effective in performance under an uncertain environment due to finding the interval-valued neutrosophic sets.

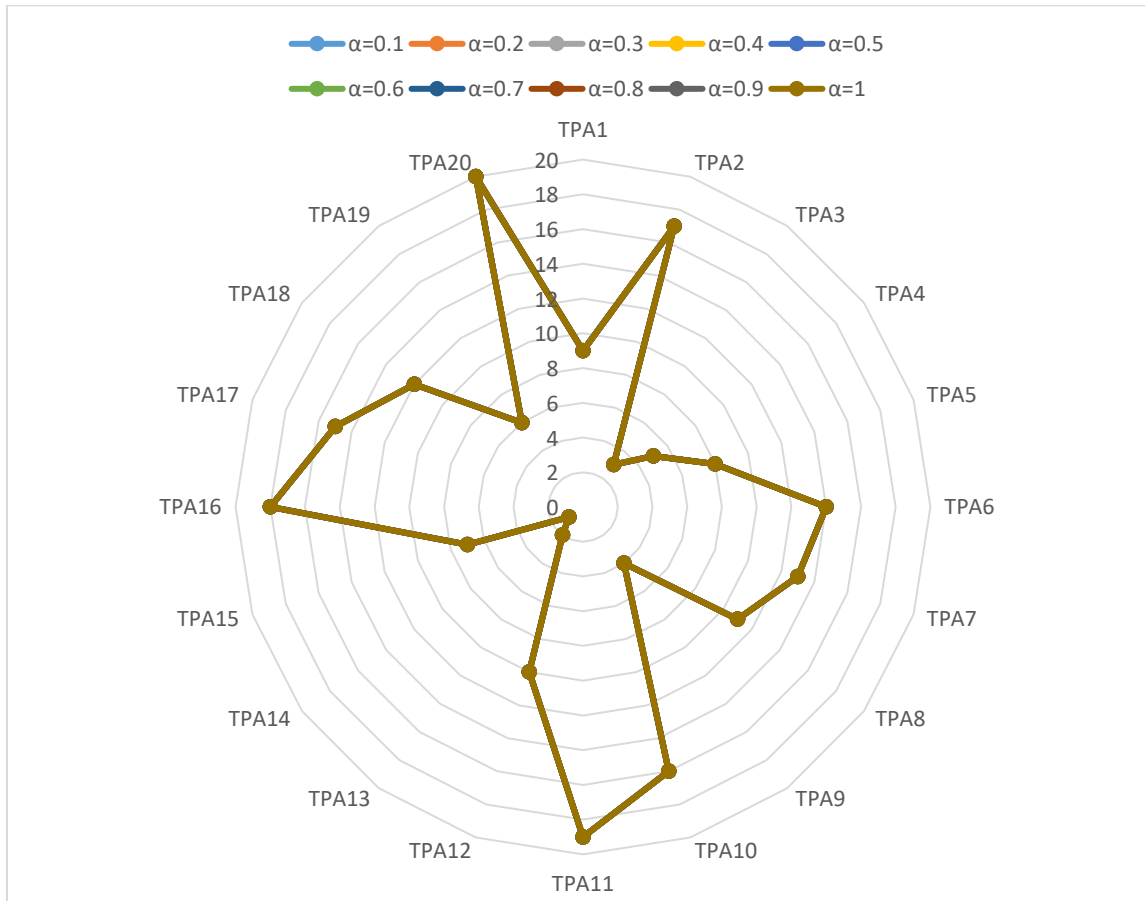


Figure 4: The rank of alternatives under value of α between 0 and 1.

5. Conclusions

A power plant's efficiency, cost, and environmental performance are all directly impacted by the fuel it uses to generate electricity. It is difficult for power plant operators and energy planners to find a fuel source that meets all their needs while being cost-effective, environmentally friendly, and efficient.

Fuel availability, price volatility, energy content, emissions profile, and technology compatibility are only a few elements that must be considered and analyzed thoroughly before a final choice can be made. The emphasis on decreasing greenhouse gas emissions and coping with climate change means that the selected fuel must be economically and environmentally sustainable.

Additionally, long-term sustainability should be taken into account while choosing fuel. There is a rising need to diversify energy sources and embrace renewable and clean energy options as limited fossil fuel supplies become more scarce. Solar, wind, hydro, and geothermal energy are all examples of renewable energy that power plants should consider adding to their fuel mix.

In this study, we employed the EDAS with the interval-valued neutrosophic sets to deal with the uncertainty information, and the EDAS method was used to rank the alternatives. We let the experts and decision-makers evaluate the criteria and alternatives. We used the interval-valued neutrosophic numbers to assess the criteria and alternatives. The weights are determined for the ten criteria to show the relationships between criteria. The 20 alternatives are ranked using the EDAS method under ten cases to illustrate the stability of the results. Then, the principal results show that alternative 20 is the best and alternative 14 is the worst.

References

- [1] A. Di Gianfrancesco, "The fossil fuel power plants technology," in *Materials for ultra-supercritical and advanced ultra-supercritical power plants*, Elsevier, 2017, pp. 1–49.
- [2] E. S. Rubin, C. Chen, and A. B. Rao, "Cost and performance of fossil fuel power plants with CO₂ capture and storage," *Energy policy*, vol. 35, no. 9, pp. 4444–4454, 2007.
- [3] M. D. Leonard, E. E. Michaelides, and D. N. Michaelides, "Energy storage needs for the substitution of fossil fuel power plants with renewables," *Renewable Energy*, vol. 145, pp. 951–962, 2020.
- [4] A. Mazandarani, T. M. I. Mahlia, W. T. Chong, and M. Moghavvemi, "Fuel consumption and emission prediction by Iranian power plants until 2025," *Renewable and Sustainable Energy Reviews*, vol. 15, no. 3, pp. 1575–1592, 2011.
- [5] E. I. Koysoumpa *et al.*, "The challenge of energy storage in Europe: focus on power to fuel," *Journal of Energy Resources Technology*, vol. 138, no. 4, p. 42002, 2016.
- [6] P. Oskarsson, K. B. Nielsen, K. Lahiri-Dutt, and B. Roy, "India's new coal geography: Coastal transformations, imported fuel and state-business collaboration in the transition to more fossil fuel energy," *Energy Research & Social Science*, vol. 73, p. 101903, 2021.
- [7] H. Hou, J. Wu, Y. Yang, E. Hu, and S. Chen, "Performance of a solar aided power plant in fuel saving mode," *Applied Energy*, vol. 160, pp. 873–881, 2015.
- [8] I. H. Aljundi, "Energy and exergy analysis of a steam power plant in Jordan," *Applied thermal engineering*, vol. 29, no. 2–3, pp. 324–328, 2009.
- [9] P. Thounthong, A. Luksanasakul, P. Koseeyaporn, and B. Davat, "Intelligent model-based control of a standalone photovoltaic/fuel cell power plant with supercapacitor energy storage," *IEEE Transactions on Sustainable Energy*, vol. 4, no. 1, pp. 240–249, 2012.
- [10] A. M. Wolsky, E. J. Daniels, and B. J. Jody, "CO₂ capture from the flue gas of conventional fossil-fuel-fired power plants," *Environmental Progress*, vol. 13, no. 3, pp. 214–219, 1994.
- [11] V. Tzelepi *et al.*, "Biomass availability in Europe as an alternative fuel for full conversion of lignite power plants: A critical review," *Energies*, vol. 13, no. 13, p. 3390, 2020.
- [12] K. Park, D. Shin, and E. S. Yoon, "The cost of energy analysis and energy planning for emerging, fossil fuel power plants based on the climate change scenarios," *Energy*, vol. 36, no. 5, pp. 3606–3612, 2011.
- [13] N. Zhang, F. Kong, Y. Choi, and P. Zhou, "The effect of size-control policy on unified energy and carbon efficiency for Chinese fossil fuel power plants," *Energy policy*, vol. 70, pp. 193–200, 2014.
- [14] D. Neshumayev, L. Rummel, A. Konist, A. Ots, and T. Parve, "Power plant fuel consumption rate during load cycling," *Applied Energy*, vol. 224, pp. 124–135, 2018.
- [15] W. R. Dunbar, N. Lior, and R. A. Gaggioli, "Combining fuel cells with fuel-fired power plants for improved exergy efficiency," *Energy*, vol. 16, no. 10, pp. 1259–1274, 1991.

- [16] A. Karaşan and C. Kahraman, "Interval-valued neutrosophic extension of EDAS method," in *Advances in Fuzzy Logic and Technology 2017: Proceedings of: EUSFLAT-2017–The 10th Conference of the European Society for Fuzzy Logic and Technology, September 11-15, 2017, Warsaw, Poland IWIFSGN'2017–The Sixteenth International Workshop on Intuitionistic*, Springer, 2018, pp. 343–357.
- [17] N. Nabeeh, "Assessment and Contrast the Sustainable Growth of Various 1 Road Transport Systems using Intelligent Neutrosophic 2 Multi-Criteria Decision-Making Model," *Sustainable Machine Intelligence Journal*, vol. 2, 2023.
- [18] A. Karaşan and C. Kahraman, "A novel interval-valued neutrosophic EDAS method: prioritization of the United Nations national sustainable development goals," *Soft Computing*, vol. 22, pp. 4891–4906, 2018.
- [19] M. Mohamed and K. M. Sallam, "Leveraging Neutrosophic Uncertainty Theory toward Choosing Biodegradable Dynamic Plastic Product in Various Arenas," *Neutrosophic Systems with Applications*, vol. 5, pp. 1–9, 2023.
- [20] J.-P. Fan, R. Cheng, and M.-Q. Wu, "Extended EDAS methods for multi-criteria group decision-making based on IV-CFSWAA and IV-CFSWGA operators with interval-valued complex fuzzy soft information," *Ieee Access*, vol. 7, pp. 105546–105561, 2019.
- [21] Alber S. Aziz, Moahmed Emad, Mahmoud Ismail, Heba Rashad, Ahmed M. Ali, Ahmed Abdelhafeez, Shima S. Mohamed, "An Intelligent Multi-Criteria Decision-Making Model for selecting an optimal location for a data center: Case Study in Egypt," *Journal of Intelligent Systems and Internet of Things*, Vol. 9 , No. 2 , (2023) : 23-35 (Doi : <https://doi.org/10.54216/JISIoT.090202>)
- [22] Tamer H. M. Soliman, "Neutrosophic Multi-Criteria Decision Making COMET Method for Evaluation Sustainable Electricity Generation Considering Renewable Energy Sources," *International Journal of Advances in Applied Computational Intelligence*, Vol. 4 , No. 1 , (2023) : 19-27 Doi : <https://doi.org/10.54216/IJAACI.040102>
- [23] Y. Li, J. Wang, and T. Wang, "A linguistic neutrosophic multi-criteria group decision-making approach with EDAS method.," *Arabian Journal for Science & Engineering (Springer Science & Business Media BV)*, vol. 44, no. 3, 2019.
- [24] Ahmed Abdelhafeez, Hoda K. Mohamed, "Skin Cancer Detection using Neutrosophic c-means and Fuzzy c-means Clustering Algorithms," *Journal of Intelligent Systems and Internet of Things*, Vol. 8 , No. 1 , (2023) : 33-42 (Doi : <https://doi.org/10.54216/JISIoT.080103>)
- [25] A. Karaşan, C. Kahraman, and E. Boltürk, "Interval-valued neutrosophic EDAS method: an application to prioritization of social responsibility projects," in *Fuzzy Multi-criteria Decision-Making Using Neutrosophic Sets*, Springer, 2019, pp. 455–485.
- [26] D. Stanujkić *et al.*, "A single-valued neutrosophic extension of the EDAS method," *Axioms*, vol. 10, no. 4, p. 245, 2021.
- [27] S. Ashraf, S. Ahmad, M. Naeem, M. Riaz, and M. Alam, "Novel EDAS methodology based on single-valued neutrosophic Aczel-Alsina aggregation information and their application in complex decision-making," *Complexity*, vol. 2022, 2022.
- [28] J. Fan, X. Jia, and M. Wu, "A new multi-criteria group decision model based on Single-valued triangular Neutrosophic sets and EDAS method," *Journal of Intelligent & Fuzzy Systems*, vol. 38, no. 2, pp. 2089–2102, 2020.
- [29] E. Cakmak, "Supplier Selection for a Power Generator Sustainable Supplier Park: Interval-Valued Neutrosophic SWARA and EDAS Application," *Sustainability*, vol. 15, no. 18, p. 13973, 2023.
- [30] S. Al-Saeed and N. M. AbdelAziz, "Integrated Neutrosophic Best-Worst Method for Comprehensive Analysis and Ranking of Flood Risks: A Case Study Approach from Aswan, Egypt," *Neutrosophic Systems with Applications*, vol. 5, pp. 10–26, 2023.

- [31] D. Xu, X. Cui, and H. Xian, “An extended EDAS method with a single-valued complex neutrosophic set and its application in green supplier selection,” *Mathematics*, vol. 8, no. 2, p. 282, 2020.
- [32] Alber S. Aziz, Neutrosophic Combinative Distance-based Assessment (CODAS) Method for Evaluating the Financial and Operational Performance of Shipping Companies, *International Journal of Advances in Applied Computational Intelligence*, Vol. 4 , No. 1 , (2023) : 28-36, Doi :<https://doi.org/10.54216/IJAACI.040103>
- [33] L. Han and C. Wei, “An extended EDAS method for multicriteria decision-making based on multivalued neutrosophic sets,” *Complexity*, vol. 2020, pp. 1–9, 2020.