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Einstein Aggregate Operators under Q-rung Orthopair Fuzzy Hypersoft Sets with Machine Learning

Muhammad Gulistan [1,*] and **Muhammad Abid** [2]

[1] Department of Electrical and Computer Engineering, University of Alberta, Edmonton, AB, Canada; mgulista@ualberta.ca.
[2] Department of Mathematics, North Carolina State University, Raleigh, 27606, NC, United States; mabid@ncsu.edu.

* Correspondence: mgulista@ualberta.ca.

Abstract: Thailand with its impressive 15.5% global share of renewable energy production, has a small 1% share of bitcoin mining. At the same time, the country is dealing with the severe effects of climate change, which emphasizes the necessity of taking proactive steps to solve environmental issues. This research integrates machine learning techniques and Einstein Aggregate Operators under q-rung orthopair fuzzy hypersoft set (q-ROFHS)-based multi-criteria decision-making technique to present a new method for analyzing CO2 impacts and mitigation solutions in Thailand. We evaluate the environmental impacts of bitcoin mining and the incorporation of renewable energy sources using an interdisciplinary framework, and we also calculate the associated carbon footprints. Additionally, the accuracy and effectiveness of studies on CO2 impacts and mitigation measures in Thailand are improved by machine learning algorithms that analyze large and complicated datasets to find patterns in CO2 emissions, energy consumption, and the integration of renewable energy. This article offers insightful analysis and practical suggestions for combating climate change and advancing sustainable development in Thailand and beyond. In future it's accuracy can be increased under other hybrid set structures and can be applied to sole the complex environmental and other problems.

Keywords: Carbon Footprints; Environmental Issues; Decision-Making; Bitcoin-Mining; Fuzzy Set Theory.

1. Introduction and Literature Review

Thailand finds itself at a critical crossroads between global concerns about climate change mitigation and environmental sustainability and its own energy situation. The nation exhibits its dedication to greener energy sources with a noteworthy 15.5% global share in renewable energy output. Its meager 1% stake in the emerging bitcoin mining industry, in contrast, draws attention to differences in the industry's environmental impact. Considering the global urgency to curtail carbon emissions and alleviate the consequences of climate change, Thailand's stance highlights the intricate relationship between energy generation, technical progress, and ecological responsibility. This paper explores the complex dynamics of Thailand's energy industry, looking at the country's efforts in renewable energy, the difficulties associated with bitcoin mining, and the need of taking preventative action against climate change. We seek to clarify the major variables influencing Thailand's carbon footprint via a multidisciplinary lens and map out a course for environmentally resilient development. Because of the large carbon footprint connected with cryptocurrency mining, there has been much concern about the environmental impact of cryptocurrencies. This has resulted in increased greenhouse gas emissions that are on par with small- to medium-sized countries. To tackle this environmental issue, we need to investigate renewable energy sources and move toward consensus processes that use less energy, particularly as the use of cryptocurrencies grows in popularity. Multi-Criteria decision-making (MCDM) approaches have become important tools to solve complex decision-making problems that comes with mitigating these environmental implications. Combining MCDM with cutting-edge methods such as q-rung orthopair fuzzy hypersoft sets (q-ROFHS) is a viable way to advance research on the consequences on the environment, integration of renewable energy sources, and carbon footprints related to Bitcoin mining. Using the q-ROFHS framework with machine learning tools makes it easier to navigate the ambiguities and complexity present in environmental data in an organized manner, while MCDM methodologies offer solid decision-making for optimizing tactics that lead to ecologically sustainable mining practices.

Because of their large carbon footprint, which is comparable to that of small to medium-sized countries, cryptocurrencies, and especially Bitcoin mining, are gaining attention [1, 2]. Fuzzy sets (FS), proposed by Zadeh [3], and intuitionistic fuzzy sets (IFS) by Atanassov [4], offer methods to address ambiguities in decision-making. The operations and aggregate operators (AOs) were added by Wang and Liu [5, 6]. Additionally, average, geometric, and hybrid AOs were developed by [7], and MCDM techniques were proposed by [8]. The soft sets (SS) theory, and proposed methods for addressing uncertainty, were originally developed by Molodtsov [9]. Soft set theory's basic and binary operations were proposed by Maji et al. [10]. Cagman and Enginoglu were the first to design fuzzy parametrized SS [11]. They extended its application to include making decisions in ambiguous conditions. By Ali et al. [12], SS operations and attributes were further improved. By merging FS and SS, Maji et al. [13] generated fuzzy soft sets (FSS). A novel technique for decision-making for FSS has been developed by Roy and Maji [14] to address the problem of imprecise multi-polar information. Cagman et al. [15] described AOs for FSS and provided a framework for decision-making based on them. By Feng et al., adaptability was added to FSS. Feng et al. [16] introduced the ability to adjust to FSS, and decision-making was based on weighted FSS. Maji et al. [17] offered fundamental operations and intuitionistic fuzzy soft sets (IFSS) for further development. In [18], IFSS operations were defined. Arora and Gard [19] presented similarity measures and weighted similarity measures in addition to describing the IFSS's fundamental concepts. Yager introduced the idea of an orthopair fuzzy set [20] and Liu and Wang [21] introduced AOs along with the decision-making process. The concept of q-rung orthopair has gained popularity as an effective method to deal with situations involving imprecise decision-making. HSS stands for hypersoft sets, and Smarandache [22] introduced the concept initially. Considering its ability to bring into account interconnected ideas such as SS and parameter sub-attributes. There are many hybrids of HSS, and each has its own method for making decisions. Neutrosophic hypersoft sets (NHSs) were defined by [23], their distance and similarity measures were proposed along with applications in decision-making issues by [24-26]. The machine learning approach in conjunction with NHS-based similarity measures was proposed by [27]. By [28], the idea has been expanded to include fuzzy reasonably aggregate operators in addition to material selection applications. Khan et al. [29] originally described q-rung orthopair fuzzy hypersoft sets (q-ROFHS), which have simple operations. AOs were proposed by [30-31], and [32-33] proposed the applications in addition to the extensions of Einstein operators. By [34], this idea has been expanded even further to include the hybrid intellectual framework known as complex q-ROFHS. To overcome uncertainties and data shortages, the new structure integrates several sources into a single value, which is critical to decision making. By analyzing large datasets to identify patterns and trends in energy consumption, carbon emissions, and renewable energy generation, machine learning plays a crucial role in reducing the environmental impact of cryptocurrency mining and integrating renewable energy sources. This method also provides valuable insights for decision-making. Owing machine learning capabilities, stakeholders may effectively design mitigation efforts and anticipate environmental implications by forecasting future patterns in energy demand and emissions. Reducing carbon emissions and boosting sustainability, machine learning algorithms find inefficiencies, optimize energy use in mining operations, and suggest energy-saving solutions.

- The paper presents the Einstein Aggregate Operators under q-rung orthopair fuzzy hypersoft sets, definitions, theorems are proposed in this paper.
- This research makes it possible to analyze and forecast how renewable energy use, Bitcoin mining, and carbon emissions will interact in Thailand, which is currently the top ten largest country to produce green energy.
- The proposed MCDM techniques are applied in this procedure. DM tools can optimize mining strategies for environmental sustainability, provide predictive modeling for future carbon footprints based on historical data, and support decision-making systems that evaluate the feasibility and economics of sustainability measures by identifying efficient energy sources.
- The proposed method with the implementation of machine learning, supports sustainability while reducing negative effects and promoting environmental goals. The results demonstrate the consistency and effectiveness of our method for handling complicated information inside the q-ROFHS's framework.

Therefore, combining q-ROFHS with the MCDM method and machine learning tools creates a powerful synergy that makes it possible to investigate and lessen the environmental impact of Bitcoin mining in a thorough manner. The organization of the research paper is structured in the following manner: Section 2 provides the basis of q-ROFHS. In Section 3, we present some fundamental operators and properties of Einstein aggregate operators for q-ROFHS. Section 4 offers a well-defined framework for MCDM that utilizes the q-ROFHS-based AHP algorithm. This framework is further illustrated by means of a case study. The findings of the study and their implications are concisely outlined in Section 5, culminating in a discussion of possible avenues for further research.

2. Preliminaries

In this section, we present some necessary definitions, which will be helpful to understand the rest of the paper.

Definition 2.1 [9, 10]. Consider $\mathfrak{B}, \breve{\mathcal{U}},$ and $\mathcal{P}(\breve{\mathcal{U}})$ be the set of attributes, universe of discourse, and power set of universes, respectively. Let $\mathfrak{A} \subseteq \mathfrak{E}$ then the pair $(\mathcal{W}, \mathfrak{E})$ is said to be an SS over the universe. Mathematically:

$$\mathcal{W} : \mathfrak{B} \to \mathcal{P}(\breve{\mathcal{U}}), \tag{1}$$

and defined as:

$$(\mathcal{W}, \mathfrak{E}) = \{\mathcal{W}(\mathrm{e}) \in \mathcal{P}(\breve{\mathcal{U}}) : e \in \mathfrak{E}\}. \tag{2}$$

Definition 2.2 [13]. Consider $\mathfrak{B}, \breve{\mathcal{U}},$ and $\mathcal{P}(\breve{\mathcal{U}})$ be the set of attributes, universe of discourse, and power set of universes, respectively. Let $\mathfrak{A} \subseteq \mathfrak{E}$ then the pair $(\mathcal{W}, \mathfrak{E})$ is said to be an FSS over the universe. Mathematically:

$$\mathcal{W} : \mathfrak{B} \to \mathcal{P}(\breve{\mathcal{U}}), \tag{3}$$

and defined as:

$$(\mathcal{W}, \mathfrak{E}) = \{\mathcal{W}(\mathrm{e}) \in \mathcal{P}(\breve{\mathcal{U}}) : e \in [0,1]\}. \tag{4}$$

Definition 2.3 [22]. The pair $(\mathcal{W}, \mathfrak{H})$ is called an HSS over $\breve{\mathcal{U}}$, where $\mathfrak{H}$ is the cartesian product of n disjoint sets $\mathfrak{H}_1, \mathfrak{H}_2, \mathfrak{H}_3, \ldots, \mathfrak{H}_{\mathrm{p}}$ having attribute values of p distinct attributes $\mathfrak{H}^1, \mathfrak{H}^2, \mathfrak{H}^3, \ldots, \mathfrak{H}^{\mathrm{p}}$, respectively. Mathematically:

$$\mathcal{W} : \mathfrak{H} \to \mathcal{P}(\breve{\mathcal{U}}). \tag{5}$$

Definition 2.4 [29]. Consider $\mathfrak{H}, \breve{\mathcal{U}},$ and $\mathcal{P}(\breve{\mathcal{U}})$ be the set of attributes, universe of discourse, and power set of universes, respectively. Let $\mathfrak{H} = \{\mathfrak{H}^1, \mathfrak{H}^2, \mathfrak{H}^3, \ldots, \mathfrak{H}^{\mathrm{p}}\}$ $(\mathrm{p} \geq 1)$, then assume $\mathrm{q-ROHS}$ be a collection of all q-rung orthopair subsets over $\breve{\mathcal{U}}$. Then the pair $(\mathcal{W}, \mathfrak{H}^1 \times \mathfrak{H}^2 \times \mathfrak{H}^3 \times \ldots \times \mathfrak{H}^{\mathrm{p}}) = (\mathcal{W}, \mathfrak{H})$ is known as q-ROHS. Mathematically:

$$\mathcal{W} : \mathfrak{H}^1 \times \mathfrak{H}^2 \times \mathfrak{H}^3 \times \ldots \times \mathfrak{H}^{\mathrm{p}} = \mathfrak{H} \to \mathcal{P}(\breve{\mathcal{U}})\ \mathrm{q-ROHS}, \tag{6}$$

and defined as $(\mathcal{W},\ \mathfrak{H}) = \{(\mathcal{T}_{\mathcal{W}}(\mathrm{e}), \mathcal{J}_{\mathcal{W}}(\mathrm{e})) : \mathrm{e} \in \mathfrak{H}\}$, where $(\mathcal{T}_{\mathcal{W}}(\mathrm{e}), \mathcal{J}_{\mathcal{W}}(\mathrm{e}))$ represent membership and non-membership of attributes, respectively, such that $0 \leq (\mathcal{T}_{\mathcal{W}}(\mathrm{e}))^{\mathrm{q}} + (\mathcal{J}_{\mathcal{W}}(\mathrm{e}))^{\mathrm{q}} \leq 1$.

Definition 2.5 [29]. Consider $\mathfrak{H}, \breve{\mathcal{U}}$, and $\mathcal{P}(\breve{\mathcal{U}})$ be the set of attributes, universe of discourse, and power set of universes, respectively. Let $\mathfrak{H} = \{\mathfrak{H}^1, \mathfrak{H}^2, \mathfrak{H}^3, \ldots, \mathfrak{H}^{\mathrm{p}}\}$, $(\mathrm{p} \geq 1)$, then assume $\mathrm{q}-\mathrm{ROFHS}$ be a collection of all q-rung orthopair subsets over $\breve{\mathcal{U}}$. Then the pair $(\mathcal{W},\ \mathfrak{H}^1 \times \mathfrak{H}^2 \times \mathfrak{H}^3 \times \ldots \times \mathfrak{H}^{\mathrm{p}}) = (\mathcal{W},\ \mathfrak{H})$ is known as q-ROFHS. Mathematically:

$$\mathcal{W}\colon\ \mathfrak{H}^1 \times \mathfrak{H}^2 \times \mathfrak{H}^3 \times \ldots \times \mathfrak{H}^{\mathrm{p}} = \mathfrak{H} \rightarrow \mathcal{P}(\breve{\mathcal{U}})\ \mathrm{q}-\mathrm{ROFHS}, \tag{7}$$

and defined as $(\mathcal{W},\ \mathfrak{H}) = \{(\mathcal{T}_{\mathcal{W}}(\mathrm{e}), \mathcal{J}_{\mathcal{W}}(\mathrm{e})) : \mathrm{e} \in \mathfrak{H} \text{ and } (\mathcal{T}_{\mathcal{W}}(\mathrm{e}), \mathcal{J}_{\mathcal{W}}(\mathrm{e})) \in [0,1]\}$, where $(\mathcal{T}_{\mathcal{W}}(\mathrm{e}), \mathcal{J}_{\mathcal{W}}(\mathrm{e}))$ represent membership and non-membership of attributes, respectively, such that $0 \leq (\mathcal{T}_{\mathcal{W}}(\mathrm{e}))^{\mathrm{q}} + (\mathcal{J}_{\mathcal{W}}(\mathrm{e}))^{\mathrm{q}} \leq 1$.

3. Einstein Aggregate Operators for q-rung Orthopair Fuzzy Hypersoft sets

In this section we present the definition and aggregate operators for q-rung Orthopair Fuzzy Hypersoft sets.

Definition 3.1. Let $A_1 = (\mathrm{K}_{R_1}, \mathrm{N}_{R_1})$, $A_2 = (\mathrm{K}_{R_2}, \mathrm{N}_{R_2})$ and $A = (\mathrm{K}_R, \mathrm{N}_R)$ are three q-ROFHS, and $\alpha > 0$, then we have Einstein based operations as follows:

$$A_1 \oplus_\varepsilon A_2 = \left(\left\langle \sqrt[p]{\frac{\mathrm{K}_{R_1}^p + \mathrm{K}_{R_2}^p}{1+\mathrm{K}_{R_1}^p \mathrm{K}_{R_2}^p}}, \frac{\mathrm{N}_{R_1}\mathrm{N}_{R_2}}{\sqrt[q]{1+\left(1-\mathrm{N}_{R_1}^q\right)\left(1-\mathrm{N}_{R_2}^q\right)}} \right\rangle\right) \tag{8}$$

$$A_1 \oplus A_2 = \left(\left\langle \frac{\mathrm{K}_{R_1}\mathrm{K}_{R_2}}{\sqrt[q]{1+\left(1-\mathrm{K}_{R_1}^p\right)\left(1-\mathrm{K}_{R_2}^p\right)}}, \sqrt[q]{\frac{\mathrm{N}_{R_1}^p + \mathrm{N}_{R_2}^p}{1+\mathrm{N}_{R_1}^p \mathrm{N}_{R_2}^p}}, \right\rangle\right) \tag{9}$$

$$\alpha.A = \left(\left\langle \sqrt[p]{\frac{\left(1+\mathrm{K}_R^p\right)^\alpha - \left(1-\mathrm{K}_R^p\right)^\alpha}{\left(1+\mathrm{K}_R^p\right)^\alpha + \left(1-\mathrm{K}_R^p\right)^\alpha}}, \frac{\sqrt[q]{2(\mathrm{N}_R)^\alpha}}{\sqrt[q]{\left(1+\mathrm{N}_R^q\right)^\alpha + (1-\mathrm{N}_R^q)^\alpha}} \right\rangle\right) \tag{10}$$

$$A^\alpha = \left(\left\langle \frac{\sqrt[\alpha]{2(\mathrm{K}_R)^\alpha}}{\sqrt[\alpha]{\left(2-\mathrm{K}_R^p\right)^\alpha + \left(\mathrm{K}_R^p\right)^\alpha}}, \sqrt[q]{\frac{(1+\mathrm{N}_R^{\mathrm{q}})^\alpha - (1-\mathrm{N}_R^{\mathrm{q}})^\alpha}{(1+\mathrm{N}_R^{\mathrm{q}})^\alpha + (1-\mathrm{N}_R^{\mathrm{q}})^\alpha}} \right\rangle\right) \tag{11}$$

Definition 3.2. Let $A_1 = (\mathrm{K}_{R_1}, \mathrm{N}_{R_1})$ and $A_2 = (\mathrm{K}_{R_2}, \mathrm{N}_{R_2})$ two q-ROFHS, and $\alpha > 0$, then we have Einstein union and intersection defined as follows:

1. $A_1 \vee A_2 = (\max(\mathrm{K}_{R_1}, \mathrm{K}_{R_2}), \min(\mathrm{N}_{R_1}, \mathrm{N}_{R_2}))$
2. $A_1 \wedge A_2 = (\min(\mathrm{K}_{R_1}, \mathrm{K}_{R_2}), \max(\mathrm{N}_{R_1}, \mathrm{N}_{R_2}))$

Theorem 1. For any two α, α_1, α_2 real numbers. Then for two q-ROFHS $A_1 = (\mathrm{K}_{A_1}, \mathrm{N}_{A_1})$, and $A_2 = (\mathrm{K}_{R_2}, \mathrm{N}_{R_2})$, then Einstein sum and product are defined as follows:

1. $A_1 \oplus A_2 = A_2 \oplus A_1$
2. $A_1 \otimes A_2 = A_2 \otimes A_1$
3. $\alpha (A_1 \oplus A_2) = \alpha A_1 \oplus \alpha A_2$
4. $(\mathrm{A1} \otimes \mathrm{A2})^\alpha = A_1^\alpha \oplus A_2^\alpha$
5. $\alpha_1 A \oplus \alpha_2 A = A(\alpha_1 + \alpha_2)$
6. $\mathrm{A}^{\alpha_1} \otimes A^{\alpha_2} = A^{\alpha_1+\alpha_2}$

Definition 3.3. Let $A_ɉ$ = ($\mathrm{K}_{A_ɉ}$, $\mathrm{N}_{A_ɉ}$) (ɉ = 1,2, … m) be a set of q-ROFHS with them corresponding weight vector $\alpha_ɉ$(ɉ = 1,2, …, m) such that $\sum_{ɉ=1}^{m} \alpha_ɉ$=1 and $\alpha_{ɉɉ} \in [0,1]$. Then the operator weighted geometric operator $q - Q$ROFHSWA: $\Lambda^m \rightarrow \Lambda$ is defined as.

$$q - Q\mathrm{ROFHSW}A\ (A_1, A_2, \ldots, A_m) = \bigoplus_{ɉ=1}^{m} \alpha_ɉ A_{ɉ+1} \tag{12}$$

Theorem 2. The aggregated value obtained by $q - Q$ROFHSWA operator of q-ROFHS is still a q-ROFHS, and

$$\mathrm{q - QROFHSWA\ (A1, A2, \ldots, Am)} = \bigoplus_{ɉ=1}^{m} \alpha_ɉ A_{ɉ+1}$$

$$= \left(\left\langle \sqrt[p]{\frac{\prod_{ɉ=1}^{m}\left(1+\mathrm{K}_{R_ɉ}^{p}\right)^{\alpha_ɉ} - \prod_{ɉ=1}^{m}\left(1-\mathrm{K}_{R_ɉ}^{p}\right)^{\alpha_ɉ}}{\prod_{ɉ=1}^{m}\left(1+\mathrm{K}_{R_ɉ}^{p}\right)^{\alpha_ɉ} + \prod_{ɉ=1}^{m}\left(1-\mathrm{K}_{R_ɉ}^{p}\right)^{\alpha_ɉ}}}, \frac{\left(\sqrt[q]{2}\right)\prod_{ɉ=1}^{m}\left(\mathrm{N}_{R_ɉ}\right)^{\alpha_ɉ}}{\sqrt[q]{\left(2-\mathrm{N}_{R_ɉ}^{q}\right)^{\alpha} + \prod_{ɉ=1}^{m}\left(\mathrm{N}_{R_ɉ}\right)^{\alpha_ɉ}}} \right\rangle\right) \tag{13}$$

Theorem 3. (Idempotency) If the q-ROFHS Aɉ = (υAɉ , Aɉ) (ɉ = 1,2, … , m) are identical, i.e., be a $A_ɉ$ = A for all ɉ, where A = (υ_A, A_A), then $q - Q$ROFHSWA(A_1, A_2, … , A_m) = A.

Theorem 4. (Homogeneity) Let φ be a positive real number. Then, we have $q - Q$ROFHSWA (φA_1, φA_2, …, φA_m) = φ ($q - Q$ROFHSWA (A_1, A_2, … , A_m))

Theorem 5. (Monotonicity) Let {$A_ɉ$ | ɉ = 1,2, …, m} and {$A'_ɉ$ | ɉ = 1,2, …, m} be two sets of q-ROFHS, where of $A_ɉ$ = ($\mathrm{K}_{A_ɉ}$, $\mathrm{N}_{A_ɉ}$) and $A'_ɉ$ = ($\mathrm{K}'_{A_ɉ}$, $\mathrm{N}'_{A_ɉ}$) for ɉ = 1,2, … , m. If $\mathrm{K}_{A_ɉ} \leq \mathrm{K}'_{A_ɉ}$ and $\mathrm{N}_{A_ɉ} \geq \mathrm{N}'_{A_ɉ}$ for all ɉ, then

$$q - QOFEWA\ (A_1, A_2, \ldots, A_m) \leq q - QROF\mathrm{HSW}A\ (A'_1, A'_2, \ldots, A'_m) \tag{14}$$

4. MCDM Algorithm

In this section, we present an MCDM that utilizes the basics of q-ROFHSs and Einstein Aggregate Operators. This algorithm is further illustrated by solving a case study of carbon footprints associated with Bitcoin mining.

4.1 Necessary Condition

The stepwise procedure of the algorithm is presented below.
Step 1. Consider goal ($\mathcal{G}$), criteria's ($\mathcal{C}_i$), and alternative's $\mathcal{A}_j$.
Step 2. Make a $\mathcal{W}^l = [\mathcal{W}_{ij}]$ pairwise comparison matrix (e.g., criteria or alternatives).
Step 3. Calculate the weighted normalized matrix $\mathcal{N}_{ij}^{l} = [\mathcal{W}_{ij}] \times \omega_j$.
Step 4. Calculate a weighted sum $\mathcal{S}_j = \sum_{j=1}^{k} \mathcal{N}_{ij}^{l}$ for each criterion ($\mathcal{C}_i$).
Step 5. Calculate the consistency ratio and analyze the ranking.

4.2 Case Study

On a life-cycle basis, renewable energy produces between 11 and 740 gCO2 for every kWh produced, depending on the kind (solar, wind, hydro, geothermal, tidal, wave, biomass) [2]. The mining process of Bitcoin is associated with energy and blockchain networks. The amount of energy the network uses will depend on the hash rate of the entire Bitcoin network. The hash rate of a blockchain network increases with the number of computers that connect to it and process hashes (guesses) on the network. A PoW blockchain network with a high hash rate is more secure and healthy since there is less likelihood of an attack. Energy use will decrease with a lower network hash rate. The network will need more energy to mine each new block when the hash rate is higher. BTC is produced using 2.7 quadrillion computed hashes. The production of one Bitcoin can consume 663.68kWh of energy and it produces 370.17 kgCO_2 [4, 5]. Through the potential for financial gain, job development, infrastructure investment, and technical advancement, Bitcoin mining may improve the economy. Bitcoins may be earned as rewards, and miners can also invest in cutting-edge gear and data centers, stabilize the energy markets, improve technology, and promote financial inclusion (Figure 1).

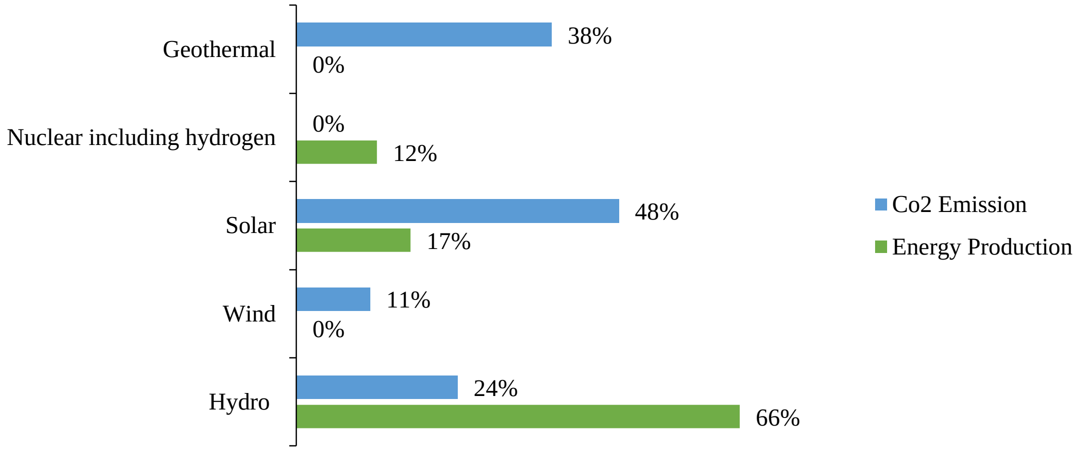


Figure 1. CO_2 emission associated with different types of energy production.

Using q-ROFHS in conjunction with Einstein Aggregate Operators and decision-making methods can improve research on the environmental effects of Bitcoin mining, the integration of renewable energy sources, and the corresponding carbon footprints. This study allows for the analysis and prediction of the interactions between carbon emissions, renewable energy use, and Bitcoin mining.

Step 1: Consider five renewable energy resources $\mathcal{R}^1$ (hydrogen), $\mathcal{R}^2$ (wind and hydro), $\mathcal{R}^3$ (solar), $\mathcal{R}^4$ (geothermal), and $\mathcal{R}^5$ (nuclear) as alternatives $\mathcal{R} = \{\mathcal{R}^1, \mathcal{R}^2, \mathcal{R}^3, \mathcal{R}^4, \mathcal{R}^5\}$. Kazakhstan has the potential to commercially gain from the cryptocurrency business, and with this study, we want to determine which renewable energy should be used to increase the Bitcoin mining process that meets its economic targets. The services of the experts in this domain were taken as decision-makers $\mathcal{D} = \{\mathcal{D}^{\mathrm{m}}\ ; m = 1,2\}$.Consider the parameter$\mathcal{P}^1 =$ cost of production, $\mathcal{P}^2 =$ Carbon footprints, and $\mathcal{P}^3 =$ economic benefits. Their respective parametric values are:

- Cost of production – $\mathcal{P}^1 = \{< \$20/MWh, < \$40/MWh, < \$80/MWh, < \$100/MWh\}$,
- Carbon footprints – $\mathcal{P}^2 = \{10 - 200\ gCO_2,\ 201 - 400\ gCO_2,\ 401 - 600\ gCO_2,\ 601 - 800\ gCO_2\}$,
- Economic benefits (per day) – $\mathcal{P}^3 = \{100\ BTC, 1000\ BTC, 10000\ BTC\}$.

Then, the function $\Gamma: \Lambda = \mathcal{P}^1 \times \mathcal{P}^2 \times \mathcal{P}^3 \longrightarrow P(\Omega)$, where $M = \{\mathcal{R}^1, \mathcal{R}^2, \mathcal{R}^3, \mathcal{R}^4, \mathcal{R}^5\} \subset \Omega$, with $\Omega = \mathcal{R}$ as the universal set. The sub-divided parametric function can be given below: $\Gamma(\$20/MWh, 140 - 400\ gCO_2,\ 100BTC) = \{\mathcal{R}^1, \mathcal{R}^2, \mathcal{R}^3, \mathcal{R}^4, \mathcal{R}^5\}$.

Step 2. Make a $\mathcal{W}^l = [\mathcal{W}_{ij}]$ pairwise comparison matrix (e.g. criteria or alternatives).
$\mathcal{D}^1$ assigned q − ROFHSs values to the parametric choices as:

$$\mathcal{W}^1 = \begin{Bmatrix} \mathcal{R}^1 < \frac{\$20\ per\ MWh}{(0.4,0.6)}, \frac{140-400\ gCO_2}{(0.9,0.7)}, \frac{100BTC}{(0.5,0.8)} >, \\ \mathcal{R}^2 < \frac{\$20\ per\ MWh}{(0.33,0.2)}, \frac{140-400\ gCO_2}{(0.12,0.27)}, \frac{100BTC}{(0.31,0.2)} >, \\ \mathcal{R}^3 < \frac{\$20\ per\ MWh}{(0.5,0.3)}, \frac{140-400\ gCO_2}{(0.4,0.5)}, \frac{100BTC}{(0.2,0.7)} >, \\ \mathcal{R}^4 < \frac{\$20\ per\ MWh}{(0.41,0.4)}, \frac{140-400\ gCO_2}{(0.7,0.3)}, \frac{100BTC}{(0.6,0.3)} >, \\ \mathcal{R}^5 < \frac{\$20\ per\ MWh}{(0.2,0.5)}, \frac{140-400\ gCO_2}{(0.3,0.6)}, \frac{100BTC}{(0.9,0.4)} > \end{Bmatrix}.$$

$\mathcal{D}^2$ defined $q-$ROFHS values to the parametric choices as:

$$\mathcal{W}^2 = \begin{Bmatrix} \mathcal{R}^1 < \frac{\$20\ per\ MWh}{(0.2,02)}, \frac{140-400\ gCO_2}{(0.5,0.4)}, \frac{100BTC}{(0.5,0.7)} >, \\ \mathcal{R}^2 < \frac{\$20\ per\ MWh}{(0.4,0.7)}, \frac{140-400\ gCO_2}{(0.9,0.7)}, \frac{100BTC}{(0.8,0.9)} >, \\ \mathcal{R}^3 < \frac{\$20\ per\ MWh}{(0.5,0.3)}, \frac{140-400\ gCO_2}{(0.7,0.7)}, \frac{100BTC}{(0.5,0.8)} >, \\ \mathcal{R}^4 < \frac{\$20\ per\ MWh}{(0.1,0.3)}, \frac{140-400\ gCO_2}{(0.6,0.3)}, \frac{100BTC}{(02,0.1)} >, \\ \mathcal{R}^5 < \frac{\$20\ per\ MWh}{(0.2,0.5)}, \frac{140-400\ gCO_2}{(0.4,0.4)}, \frac{100BTC}{(0.5,0.5)} > \end{Bmatrix}.$$

Step 3: The DM choice and expertise-based weights for each attribute were $\omega_j = (0.229, 0.471, 0.300)$.

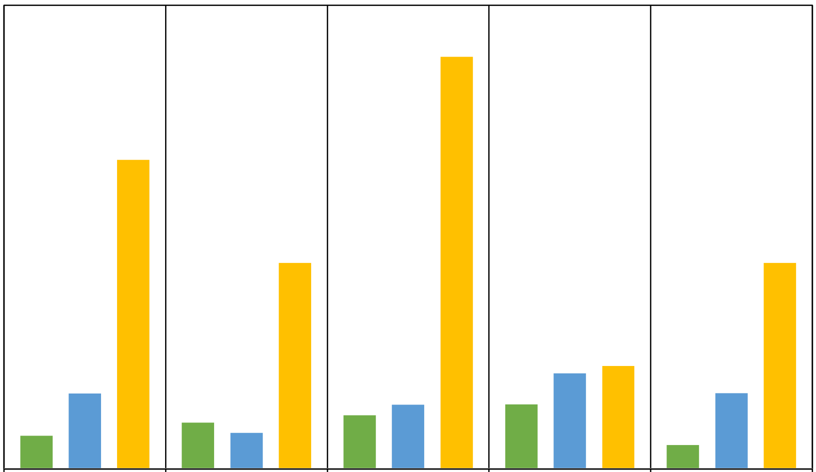
Step 4: The weighted sum $\mathcal{S}_j = \sum_{j=1}^{k} \mathcal{N}_{ij}^{l}$ for each criterion ($\mathcal{C}_i$) was given in Table 1.

Table 1. The resulting weighted sums.

Alternatives	$\mathcal{S}_1$	$\mathcal{S}_2$
$\mathcal{R}^1$	0.323	0.732
$\mathcal{R}^2$	0.452	0.352
$\mathcal{R}^3$	0.521	0.625
$\mathcal{R}^4$	0.627	0.928
$\mathcal{R}^5$	0.234	0.736

Step 5: Finally, list the alternatives with total scores max ($\mathcal{S}_i$) and rank the highest value. $Score = \{\mathcal{R}^1 < 0.732 >, \mathcal{R}^2 < 0.452 >, \mathcal{R}^3 < 0.625 >, \mathcal{R}^4 < 0.928 >, \mathcal{R}^5 < 0.736 >\}$. The ranking findings show that when using renewable energy sources to fuel Bitcoin mining, the order of efficacy is $\mathcal{R}^2 < \mathcal{R}^3 < \mathcal{R}^1 < \mathcal{R}^5 < \mathcal{R}^4$. This strategy could have two beneficial effects: (i) it could significantly lower carbon footprints, and (ii) boost economic growth. The energy-intensive nature of Bitcoin mining can be addressed by using sustainable energy sources like solar, wind, or hydroelectric power in processing processes. This change could significantly lessen the negative effects that these activities have on the environment.

Utilizing renewable energy for Bitcoin mining promotes employment and innovation in the renewable energy sector in addition to making the environment greener. This is in line with larger international efforts to tackle climate change and create a more environmentally sustainable future. The ranking results are shown in Figure 2, which provides visual evidence of the possible advantages of using renewable energy in Bitcoin mining operations.



	R1	R2	R3	R4	R5
S1	0.323	0.452	0.521	0.627	0.234
S2	0.732	0.352	0.625	0.928	0.736
Rank	3	2	4	1	2

Figure 2. Renewable energy alternative rankings.

4.3 Results Calculation Using Machine Learning

The present investigation highlights the critical significance that the incorporation of machine learning techniques plays in augmenting the precision and efficacy of our evaluation of the CO2 impacts and mitigation strategies within Thailand's environmental framework. Owing to the intricacy of the computations required and the large volume of data that needs to be processed, machine learning techniques present a potent way to extract significant insights from complicated datasets. By utilizing Python's Analytic Hierarchy Process (AHP) technique, we can efficiently prioritize mitigation measures and carry out thorough evaluations. We can find important patterns and connections that might otherwise go unnoticed by using machine learning algorithms to sort through the complexity of CO2 emissions, energy consumption patterns, and the integration of renewable energy sources. This methodology not only enhances the precision of our analysis but also promotes better-informed decision-making procedures, endowing policymakers and interested parties with the ability to execute focused interventions aimed at reducing environmental consequences and promoting sustainable development programs in Thailand and other regions.

4.4 Discussion and Comparison

In this study, we proposed the q-ROFHS-based AHP algorithm to solve MCDM problems. The formulated algorithm is more useful for prediction and implementation. The study focuses on the divided attributes, emphasizing how flexible it is to changing choice factors, attributes, and outputs for decision-makers. It emphasizes how crucial it is to rank techniques across various models so that they can be directly compared based on predictions. The study presents the result of the comparison with q-ROF hybrid set structures. It also highlights how incomplete and unclear facts are frequently included in decision-making processes, highlighting the necessity for a technique to communicate information more precisely and logically. To demonstrate the utility of the premeditated technique, we equate the achieved significance with some dominant methods under the setting q-ROFS, q-ROFSS, and q-ROFHS (Table 2). According to Table 2, the suggested approach is expected to outperform several q-ROF hybrid set structures in terms of effectiveness, importance, superiority, and improvement.

Table 2. Comparison of the proposed q-ROFHS-based AHP algorithm.

Set	MCDM algorithm	Parameterization	Sub-attributes
q-ROFS [24]	AHP	×	×
q-ROFSS [28]	AHP	✓	×
q-ROFHS [proposed]	AHP	✓	✓

The efficacy of methods for mitigating pollution is contingent upon optimization algorithms that include variables like economic viability and the incorporation of sustainable energy sources. Decision support systems that use AHP provide stakeholders with data-driven insights. The passage is in line with the problems that cryptocurrency mining poses for the environment in this context, especially because of the heavy reliance on fossil fuels and non-renewable energy sources that result in large carbon footprints. The suggested method highlights the special qualities of q-ROFHS and associated AOs as essential instruments for decision-making in reducing the carbon footprint issues related to Bitcoin mining to meet this urgency.

5. Conclusion

This study concludes by highlighting the crucial relationship that exists in Thailand between the use of renewable energy, bitcoin mining, and environmental sustainability. Even while Thailand produces a noteworthy amount of renewable energy globally, the country's small fraction of bitcoin mining activities highlights the urgent need for aggressive environmental measures, particularly given the devastating effects of climate change. This research offers a novel methodology for analyzing CO2 impacts and identifying mitigation solutions specific to Thailand's environmental challenges by combining machine learning techniques and Einstein Aggregate Operators within a q-rung orthopair fuzzy hypersoft set (q-ROFHS)-based multi-criteria decision-making framework. We have assessed the environmental effects of bitcoin mining and the possible advantages of incorporating renewable energy sources into the country's energy infrastructure through interdisciplinary collaboration. Our results highlight how crucial it is to precisely measure the carbon footprints of different activities, like mining bitcoin, and how important it is to use renewable energy to lessen these effects. In addition, we have improved the accuracy and efficacy of our study by utilizing machine learning algorithms, which has allowed us to find complex patterns in CO2 emissions, energy consumption trends, and the integration of renewable energy sources. In addition to providing insightful information about Thailand's environmental situation, this report makes actionable suggestions for halting climate change and advancing sustainable development on a national and international scale. In the future, we could improve and broaden our approach by investigating different hybrid set structures and utilizing them to tackle environmental difficulties and other relevant matters. In the end, we can enable decision-makers, stakeholders, and communities to take immediate action and make well-informed decisions toward a more sustainable future for Thailand and beyond by implementing a thorough and data-driven strategy.

Declarations

Ethics Approval and Consent to Participate

The results/data/figures in this manuscript have not been published elsewhere, nor are they under consideration by another publisher. All the material is owned by the authors, and/or no permissions are required.

Consent for Publication

This article does not contain any studies with human participants or animals performed by any of the authors.

Availability of Data and Materials

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Competing Interests

The authors declare no competing interests in the research.

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