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OPA-IF-Neutrosophic-TOPSIS Strategy under SVNS Environment Approach and Its Application to Select the Most Effective Control Strategy for Aquaponic System

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Abstract. The accelerated progress of aquaponics offers a promising remedy for food production in arid regions, where success heavily hinges on sustaining optimal water quality parameters of aquaponic system. However, managing water parameters in large-scale aquaponic farms, given their complex and interconnected nature, poses significant challenges. Various control approaches have been introduced over the years, but selecting the most suitable one is vital for ensuring stability, efficiency, and high productivity. In this study, a novel fuzzy-based Multiple Criteria Decision Making (MCDM) methodology is proposed, which combines the Intuitionistic Fuzzy Ordinary Priority Approach (OPA-IF) with the Neutrosophic-TOPSIS strategy. This methodology aims to identify the most appropriate control strategy for large-scale aquaponic systems. The OPA-IF analysis reveals that the 'Capability to Handle MIMO Systems' is the most critical criterion, leading to the conclusion, through the Neutrosophic-TOPSIS approach, that 'Model Predictive Control (MPC)' is the optimal choice for managing large-scale aquaponic systems. Additionally, a comparative analysis using the BWM-Neutrosophic-TOPSIS strategy further supports the findings of the proposed method. The results are further validated through statistical analysis and sensitivity testing, ensuring their robustness and reliability. Overall, this study not only contributes to the scientific understanding of control strategies in aquaponics but also offers practical insights for farmers and aquaponic practitioners. The ultimate goal is to enhance the sustainability and efficiency of aquaponic systems, promoting their adoption and long-term success in sustainable food production.

Key words: OPA-IF, TOPSIS, neutrosophic sets, aquaponic systems, control strategy.

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1. Introduction

Fulfilling the nutritional needs of an expanding global population, projected to reach 10 billion by 2050, stands as a significant global concern (Worldometer: https://www.worldometers.info/world-population/ "Accessed 5 Feb 2024"). Various factors such as the COVID-19 pandemic, conflicts, and erratic weather patterns due to climate change have hindered progress toward achieving the first Millennium Development Goal of eradicating extreme poverty and hunger (WHO, 2000. Millennium Development Goals (MDGs) [WWW Document]: https://www.who.int/topics/millennium_development_goals/about/en/. Accessed 29 Nov 2000). The report from the State of Food Security and Nutrition in the World (SOFI) indicates that since 2019, an additional 122 million people have faced hunger, with the global hunger rate stabilizing between 2021 and 2022 but persistent crises in many regions prompting calls for international action to address underlying causes (Ewan Thomson. This is the state of food security in 2023: https://www.weforum.org/agenda/2023/08/food-security-hunger-global/. Accessed 2 August 2023). Meeting the increased food demands necessitated by a nearly 30% population growth requires a potential 50% rise in global food production (Ivanovich *et al.*, 2023). However, various challenges such as natural disasters, climate change, land degradation, rapid urbanization, unfair trade practices, and others have significantly impeded food production rates (Basumatary *et al.*, 2023). According to forecasts by Kumar *et al.* (2023), even with endeavours aimed at enhancing crop yields and refining production methodologies, current trajectories indicate that the global food demand might not be satisfied by 2050. Climate change alone is projected to lead to the loss of up to 18% of arable land by the end of the century, exacerbating food insecurity in vulnerable regions (Qiu *et al.*, 2023). These challenges underscore the growing need for innovative practices, systems, and methods in the food production industry.

As a practical response to food and environmental challenges, aquaponics farming is gaining increasing recognition as a means to rapidly boost food production without harming the environment. Aquaponics represents an eco-friendly and sustainable approach to food production, leveraging the principles of the circular economy and biological systems to maximize output while minimizing inputs and waste. It integrates two core production methods: aquaculture, focusing on aquatic animal breeding, primarily fish, and hydroponics, which involves growing plants without soil (refer to Fig. 1) (Baganz *et al.*, 2022). Within an aquaponic system, waste from aquatic animals is converted into organic fertilizers through microbial processes, while hydroponic plants purify the water by absorbing nutrients, thus facilitating its recycling in the fish tank (Kushwaha *et al.*, 2023). In essence, aquaponics functions as an ecosystem where fish, plants, and microbes coexist symbiotically, contributing to sustainable food production. To support crucial bacteria involved in nutrient cycling and maintain system integrity, aquaponic setups prohibit chemical additives and antibiotics, resulting in naturally healthy crops grown essentially organically (David *et al.*, 2022). Due to its closed circular nature, aquaponics enhances labour efficiency and offers potential for sustainable output growth, thereby enhancing food security and agricultural profitability (Thakur *et al.*, 2023). Compared to conventional farming,

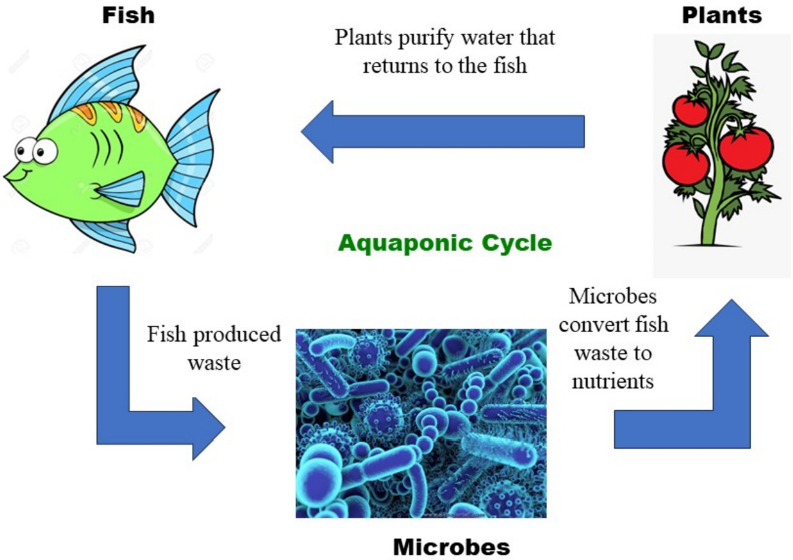

Fig. 1. The aquaponic cycle.

aquaponics requires less land and water, making it a viable solution for arid regions and contributing to economic development through its rapid production capabilities. Consequently, aquaponics emerges as an innovative, low-carbon farming technique characterized by its intensity, sustainability, circularity, and high productivity (Okomoda *et al.*, 2023).

Aquaponic systems operate within a closed-loop water environment, hosting fish, microorganisms, and plants. The physical, chemical, and biological aspects of the circulating water are crucial for the survival of all three components. Hence, it's imperative to maintain optimal water quality parameters to ensure the independent thriving of each component. Fish growth rate in aquaponics holds significant importance with implications for ecology, evolution, and conservation. Key water quality factors affecting fish growth encompass temperature, dissolved oxygen levels, water pH, ammonium concentration, nitrate levels, and more (Krastanova *et al.*, 2022). Temperature directly influences fish metabolism, impacting energy balance, behaviour, appetite, digestion, energy production, and nutrient absorption (Lindmark *et al.*, 2022). Inadequate temperatures can lead to fungal infections, affecting both juvenile and adult fish, potentially leading to egg and larvae decay (Cascarano *et al.*, 2021). Dissolved oxygen levels are critical for fish respiration, essential for their survival. Water pH also influences fish growth, with slightly acidic environments potentially impacting reproduction rates (Yanes *et al.*, 2020). Ammonia is a significant parameter in aquaponic systems, even small amounts can be highly toxic to fish, especially in strongly acidic or alkaline conditions (Levit, 2010). Nitrate levels in water also affect fish growth, particularly detrimental to fry and juvenile fish, impairing their growth (Tilak *et al.*, 2007). However, due to system dynamics and environmental factors, these parameters often deviate from ideal values, causing stress, disease, and even death in fish, affecting the productivity and sustainability of the aquaponic systems (Anando *et al.*, 2022). Moreover, these water quality parameters are interconnected. Temperature affects oxygen solubility in water, warmer water holding less dissolved oxygen (Butcher and Covington, 1995). pH influences ammonia toxicity, with its proportion of forms influenced by pH levels (Levit, 2010). Understanding these relationships underscores the importance of holistic system management in aquaponics. Maintaining optimal water quality parameters is essential for promoting optimal fish growth, ensuring a stable, well-balanced environment that meets the physiological needs of fish and supports nutrient cycling for both fish and plant health.

The nature of an aquaponic system, which integrates fish, microorganisms, and plants within a closed-loop water environment, requires effective control strategies to maintain optimal water quality parameters. As aquaponics continues to evolve and expand, especially towards industrial-scale operations, various control strategies can be implemented to ensure the success of the system. However, selecting the most appropriate control approach is crucial for achieving the best outcomes, considering some specific criteria of the aquaponic system. One essential aspect to consider when choosing control strategies is the size and scale of the aquaponic system. Smaller-scale systems may require more hands-on, manual control methods, while larger industrial systems can benefit from automated or semi-automated control systems. Automation can help monitor and regulate water quality parameters more efficiently, reducing the need for constant human intervention and ensuring consistent conditions for the aquatic and plant components (Channa *et al.*, 2024). Another factor to consider is the complexity of the system and the interrelationships between its components. Aquaponic systems are dynamic and interconnected, with changes in one component affecting others. Control strategies should account for these interactions to maintain balance and harmony within the system (Rossi *et al.*, 2024). Additionally, the specific requirements of the fish and plant species being cultivated should inform control strategies. Different species have varying tolerance levels for factors such as temperature, pH, and nutrient concentrations. Tailoring control approaches to meet the needs of the organisms within the system is essential for maximizing growth and productivity while minimizing stress and potential health issues (Lennard and Goddek, 2019). Furthermore, the availability of resources, technology, and expertise will influence the selection of control strategies. Some systems may have access to advanced monitoring equipment, data analysis tools, and specialized knowledge, allowing for more sophisticated control approaches. In contrast, others may rely on simpler, more cost-effective methods that prioritize basic water quality monitoring and manual intervention (Rossi *et al.*, 2024). Ultimately, the objective of selecting control strategies in aquaponics is to enhance system performance, productivity, and sustainability while minimizing risks and resource usage. With a plethora of options available, including ON-OFF control, open-loop control, PID control, model predictive control, rule-based control, programmable logic control, and others, determining the most suitable approach can be challenging. Consequently, ensuring long-term success and achieving desired outcomes requires careful consideration and evaluation of these various control methods and selecting the best one.

1.1. *Literature Review*

A comprehensive review of the existing literature has been conducted to identify and define the problem statement surrounding control strategies in aquaponic systems. Goddek *et al.* (2015) highlight the various challenges involved in implementing effective control strategies within aquaponic systems, emphasizing the unique complexities of these environments. Similarly, Yep and Zheng (2019) provide a review that addresses the challenges faced when applying control systems in aquaponics, noting the intricate nature of the system and the difficulties in achieving effective regulation. Okomoda *et al.* (2023) offer an in-depth discussion of the challenges associated with the adoption of aquaponics, focusing on the inherent complexities such as nonlinear behaviour, the Multi-Input Multi-Output (MIMO) characteristics of the system, and other system-specific intricacies. Additionally, Ng and Mahkeswaran (2024) examine the technological barriers in aquaponic systems, which further complicate the implementation of control strategies, thus limiting their potential for optimization. Through this extensive analysis, it became evident that, given the complexities and challenges identified in the literature, there is a pressing need to explore and identify suitable control approaches that can address the unique needs of large-scale aquaponic systems. The ultimate objective of the study is to enhance the production efficiency, profitability, and sustainability of aquaponic systems—goals that cannot be achieved without the effective implementation of control strategies. Therefore, addressing this issue and selecting the most appropriate control strategy for large-scale applications is the central focus of our research.

In recent years, there has been a notable increase in proposals for control mechanisms designed specifically for aquaponic systems. These mechanisms employ a variety of strategies, including ON-OFF control, Rule-based control, Open-loop control, PID (Proportional Integral Derivative), MPC (Model Predictive Control), and PLC (Programmable logic control), each offering unique advantages and applications. However, a significant portion of these proposals focuses on small-scale aquaponic setups, such as kitchen gardens, indoor aquaponic farming, and balcony gardening. In response to the growing interest in small-scale aquaponics, researchers have begun integrating Artificial Intelligence (AI) and Internet of Things (IoT) technologies with traditional ON-OFF control methods. For instance, Vernandhes *et al.* (2017) introduced a smart aquaponics monitoring and control system utilizing a sensor network for water quality parameters, managed through a microcontroller. Similarly, Dutta *et al.* (2018) and Zamora-Izquierdo *et al.* (2019) integrated IoT technology and sensor networks to regulate water quality parameters. Khaoula *et al.* (2021) implemented an IoT-based solution for monitoring and controlling water quality and environmental parameters using sensors for water level, temperature, and CO_2, along with actuators. Additionally, Channa *et al.* (2024) explored the integration of Artificial Intelligence and IoT in a smart aquaponics system to monitor and control essential parameters using Rule-based Control approach. While, much of the focus remains on control mechanisms for small-scale aquaponic systems, there is also emerging interest in applying machine learning techniques for aquaponic setups. Debroy and Seban (2022a, 2022b) proposed prediction methods for fish weight estimation using Artificial Neural Network

(ANN) and its hybrid with fuzzy logic (ANFIS), as well as ANN models for predicting tomato biomass in aquaponic systems, respectively. Eneh *et al.* (2023) presented a yield prediction method for aquaponic systems employing various machine learning algorithms. Furthermore, Rajendiran and Rethnaraj (2024) discussed a study on IoT-integrated Machine Learning-based Indoor Aquaponics farming.

Recent studies have focused on employing PID (Proportional Integral Derivative) control strategies in aquaponics to efficiently regulate specific water quality parameters. For example, Alipon *et al.* (2021) introduced a design for an automated fertigation system that monitors photoperiod and nutrient consumption, employing a Proportional-Integral-Derivative (PID) system. Li *et al.* (2022) applied PID control to regulate dissolved oxygen concentration in aquaponic recirculating water. Kim *et al.* (2023) presented a Dissolved Oxygen (DO) management system for aquaponic systems using PI and PID controllers. Kannabiran *et al.* (2024) suggested that a PI controller demonstrated robustness in maintaining pH levels within the desired range under varying operating conditions. Wei *et al.* (2019) proposed a laboratory-based aquaponic system utilizing PLC (Programmable Logic Controller) and LabVIEW. Another study by Selvalakshmi *et al.* (2023) developed a PLC-based approach for a small-scale aquaponic system. Chahid *et al.* (2021) conducted a comparative analysis of four Model Predictive Control (MPC) strategies for fish growth reference tracking using a representative bioenergetic growth model in precision aquaculture. Ding *et al.* (2018) explored the opportunities and challenges associated with implementing MPC in aquaponic systems. Lin *et al.* (2020) proposes the use of open-loop control and Model Predictive Control (MPC) for managing greenhouse parameters. Similarly, Debroy *et al.* (2024a) present an MPC-based strategy for controlling aquaponic greenhouse parameters, and they also provide a comparison of this approach with a traditional PI controller. Another publication by Debroy *et al.* (2024c) presents a similar MPC-based strategy, but for controlling water quality parameters in aquaponic systems, and again, they compare this method with a conventional PI controller. In a recent study by Debroy *et al.* (2024b), the authors employed Multi-Criteria Decision Making (MCDM) techniques to identify the most suitable water quality parameter for an aquaponic system. Their research aimed to evaluate and prioritize various water quality indicators by considering multiple criteria, ultimately selecting the one most critical for ensuring the optimal functioning and sustainability of aquaponics. The application of MCDM in this context provides a structured approach to decision-making, helping to balance and assess the different factors that influence water quality in aquaponic environments.

1.2. *Research Gap*

The existing literature clearly demonstrates the profound impact of integrating aquaculture and hydroponics within aquaponics systems on the reliance of fish growth and yield on water quality parameters. Maintaining these parameters at optimal levels is imperative for the success and productivity of aquaponic systems. However, previous research has predominantly focused on monitoring and controlling small-scale smart aquaponics setups, often employing various control approaches. While some studies have ventured into incorporating IoT-based machine learning methods to predict yields and manage system parameters, the diverse array of control approaches utilized poses a significant challenge in determining the most suitable one for broader application in aquaponic systems. This variability in control strategies further complicates the selection process, particularly when considering implementation in larger-scale aquaponic operations. Moreover, the predominant emphasis on small-scale setups in past research exacerbates the difficulty in identifying the ideal control approach for industrial-scale aquaponics. The lack of specific research tailored to the unique requirements and complexities of large-scale systems underscores a notable gap in the current literature. Consequently, a critical research question arises: *Which control strategy is most pertinent for implementation in large-scale aquaponic systems*?

Addressing this research gap is paramount for advancing our understanding of optimal control strategies tailored to industrial-scale aquaponics. Such advancements are vital for improving the sustainability, productivity, and viability of large-scale aquaponic operations in real-world applications. Therefore, bridging this gap is essential for driving progress in the field and ensuring the successful integration of aquaponics into broader agricultural practices.

1.3. *Objective of the Study*

Aquaponics stands as a sustainable farming method, marrying aquaculture with hydroponics to create a harmonious ecosystem. In this system, fish waste provides nutrients for plants, while plants filter and purify the water for the fish. Given the intricate balance required, understanding water quality parameters is paramount, as they directly impact the health and growth of both fish and plants. However, these parameters are susceptible to fluctuations due to external factors and are interrelated, necessitating a careful balance. To tackle these challenges, a robust control strategy is imperative. Moreover, with aquaponics poised for larger-scale adoption, selecting the optimal control approach is crucial, given its promising future prospects. Therefore, the primary objective of this study is to determine the most effective control strategy tailored specifically for industrial-scale aquaponic systems. The overarching goal is to optimize production, enhance system stability, and maximize profitability within these large-scale operations. By identifying the most effective control strategy tailored to the unique requirements of industrial-scale aquaponic systems, this study aims to drive advancements in aquaponic technology and contribute to the sustainable development of agriculture. Ultimately, the findings of this research have the potential to significantly impact the future of food production by enabling the scalable and profitable implementation of aquaponic systems on a large scale. Advancing aquaponic systems through effective control measures holds immense promise in addressing the looming challenges of global food demands and hunger. It can significantly contribute to enhancing food security worldwide by providing a sustainable and efficient method of agricultural production. Thus, the elaboration of this study underscores its potential to revolutionize food production practices and address critical global challenges.

This study aims to introduce a novel hybrid Multiple Criteria Decision Making (MCDM) model tailored to identify the most effective control approach for large-scale aquaponic systems. The proposed approach, named OPA-IF-Neutrosophic-TOPSIS under SVNS Environment, integrates various decision-making techniques into a cohesive framework—a concept not yet explored in existing literature. In this hybrid model, criteria weights are determined using the Intuitionistic Fuzzy ordinal priority Approach (OPA-IF). Subsequently, the ranking of alternatives is refined through the use of TOPSIS within a Neutrosophic fuzzy environment. This comprehensive methodology provides a fresh perspective on optimizing decision-making processes in aquaponic systems by synergistically leveraging diverse analytical tools.

In 2020, Ataei *et al.* introduced the MCDM method known as OPA (Ordinal Priority Approach), representing a departure from traditional pairwise comparisons. Building upon this, Mahmoudi *et al.* (2022) developed OPA-F (Fuzzy ordinal priority Approach) in 2022. This approach eliminates the need for pairwise comparisons, automatically estimates attribute weights, and integrates observations without averaging them. However, traditional fuzzy sets face challenges in precisely determining membership mappings, particularly under specific circumstances (Chiao, 2016). To address this limitation, intuitionistic fuzzy sets (IFSs) were introduced. IFSs specify both membership and non-membership degrees of elements within a fuzzy set, thereby accommodating ambiguity levels (Jin *et al.*, 2016; Wan *et al.*, 2016). In 2024, Majumder and Salomon introduced the Intuitionistic Fuzzy Ordinal Priority Approach (OPA-IF) to better handle uncertainty in decision-making. This method extends the traditional OPA and OPA-F by using triangular intuitionistic fuzzy sets (TIFS) instead of standard fuzzy sets, addressing challenges in determining exact membership values. Unlike OPA-F, OPA-IF relies on ranks rather than weights for criteria, offering a more flexible approach. The study combines OPA-IF with the OPA-F method to improve Multi-Criteria Decision-Making (MCDM) in aquaponic systems, effectively managing ambiguity and optimizing decision outcomes.

In this study, the TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method, as delineated in the primary reference (Hwang *et al.*, 1981), is utilized to ascertain the optimal option. The process of assigning criteria weights is guided by TrF-FOCUM (Majumder, 2023), facilitating this determination. The rationale for opting for Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) stems from its user-friendly interface and its adaptability to meet both qualitative and quantitative requirements. By evaluating each option based on its best and worst outcomes, TOPSIS contributes to a more robust ranking outcome. Furthermore, it can incorporate cost-benefit considerations, rendering it suitable for scenarios where the interaction between performance and cost is significant. While previous research has extensively delved into fuzzy and intuitionistic fuzzy Multiple Criteria Decision Making (MCDM) problems, the growing recognition of ambiguity's role in MCDM complexities highlights the need to incorporate Neutrosophic sets. Neutrosophic sets are adept at addressing environments characterized by uncertainty, indeterminacy, and inconsistency within the MCDM methodology. Despite the attention dedicated to challenges posed by fuzzy and intuitionistic fuzzy MCDM, integrating indeterminacy into the realm of MCDM complexities is deemed crucial. In 2023, Neutrosophic-TOPSIS was developed by Pramanik *et al.* (2023) to determine alternative rankings, marking a significant advancement in tackling the intricacies of decision-making under uncertainty.

1.4. *Advantage and Novelty*

The hybrid approach that integrates the Neutrosophic-TOPSIS strategy for assessing alternative levels within a Single Valued Neutrosophic (SVN) framework with the Intuitionistic Fuzzy-Ordinary priority approach (OPA-IF) for evaluating criteria levels offers numerous advantages:

I. This method adeptly manages uncertainty within SVN contexts by leveraging both OPA-IF and Neutrosophic logic. Neutrosophic logic addresses uncertainty at the alternative level, while OPA-IF tackles uncertainty at the criteria level, ensuring comprehensive treatment of ambiguity throughout decision-making.
II. By eliminating the need for pairwise comparisons among attributes, this paradigm streamlines the decision-making process, making it more straightforward and efficient.
III. The Neutrosophic-TOPSIS technique boosts the decision-making process's resilience to ambiguity by explicitly considering degrees of truth, indeterminacy, and falsehood at the alternative level. This ensures the reliability of decision outcomes, even amidst unclear or ambiguous information.
IV. Adopting a multi-criteria approach enhances the generation of logical and dependable conclusions, especially in scenarios with unclear or inconsistent input parameters.
V. Beyond providing a novel approach for multi-criteria evaluation, the MCDM tool fosters sound and productive decision-making by promoting logical and evidence-based reasoning.
VI. Addressing expert bias poses a significant challenge in decision-making, particularly in subjective scenarios or when experts lack sufficient knowledge or experience. In such cases, traditional pairwise comparison methods may yield unreliable or inconsistent results, undermining the process's credibility and reliability.
VII. The MCDM technique evaluates and ranks control approaches in a Neutrosophic manner. It is noteworthy that employing various fuzzy set extensions, such as hesitant, spherical, and picture, may introduce specific additional constraints or limitations.

2. Initial Preparations

The Preliminary section comprises two segments: the first delves into Intuitionistic Fuzzy Sets (IFS), while the second explores Single Valued Neutrosophic Sets (SVNS), outlined in Sections 2.1 and 2.2, respectively.

2.1. *Preliminary of IFS*

Fuzzy Sets (FS), as introduced by Zadeh (1965), along with Intuitionistic Fuzzy Sets (IFS), pioneered by Atanassov and Stoeva (1986), or their extensions, are commonly employed to manage information characterized by incompleteness and imprecision. Mardani *et al.* (2015) offer an outline of various fuzzy Multiple Criteria Decision Making (MCDM) methodologies. Within this framework, several fundamental notions are utilized in constructing OPA-IF.

Definition 1. Assuming $Z \neq \{\,\}$ is a set, the intuitionistic fuzzy set in Z has the property Y given by, $\tilde{Y} = \{\langle y, \alpha_{\tilde{Y}}(y), \beta_{\tilde{Y}}(y)\rangle; y \in Y\}$ as long as, $\alpha_{\tilde{Y}} : Z \rightarrow \{0, 1\} \cup (0, 1)$ and $\beta_{\tilde{Y}} : Z \rightarrow \{0, 1\} \cup (0, 1)$ meet the condition $\alpha_{\tilde{Y}}(y) + \beta_{\tilde{Y}}(y) \in \{0, 1\} \cup (0, 1)$.

Definition 2. Within the realm of Triangular Intuitionistic Fuzzy Numbers (TIFN), the membership function and non-membership mapping below elucidate the intuitionistic fuzzy subset $\tilde{Y}$ in the set of real numbers $\mathbb{R}$.

$$\alpha_{\tilde{Y}}(x) = \begin{cases} \dfrac{y - w^v}{w^u - w^v}, & \text{for } w^v \leqslant y \leqslant w^u, \\ \dfrac{w^t - y}{w^t - w^u}, & \text{for } w^u \leqslant y \leqslant w^t, \\ 0, & \text{otherwise;} \end{cases} \quad \text{and}$$

$$\beta_{\tilde{Y}}(x) = \begin{cases} \dfrac{w^u - x}{w^u - w'^v}, & \text{for } w'^v \leqslant y \leqslant w^u, \\ \dfrac{x - w^u}{w'^t - w^u}, & \text{for } w^u \leqslant y \leqslant w'^t, \\ 1, & \text{otherwise,} \end{cases}$$

where $w'^v \leqslant w^v \leqslant w^u \leqslant w^t \leqslant w'^t$ and $\alpha_{\tilde{Y}}(y) + \beta_{\tilde{Y}}(y) \in \{0, 1\} \cup (0, 1)$ an $\tilde{Y} = (w^v, w^u, w^t; w'^v, w^u, w'^t)$ represents TIFN.

Definition 3. If $\tilde{Y}_1 = (w_1^v, w_1^u, w_1^t; w_1'^v, w_1^u, w_1'^t)$ and $\tilde{Y}_2 = (w_2^v, w_2^u, w_2^t; w_2'^v, w_2^u, w_2'^t)$ be two TIFNs, then

(i) $\tilde{Y}_1 + \tilde{Y}_2 = \big(w_1^v + w_2^v, w_1^u + w_2^u, w_1^t + w_2^t; w_1'^v + w_2'^v, w_1^u + w_2^u, w_1'^t + w_2'^t\big)$;

(ii) $\tilde{Y}_1 \tilde{Y}_2 = \big(w_1^v w_2^v, w_1^u w_2^u, w_1^t w_2^t; w_1'^v w_2'^v, w_1^u w_2^u, w_1'^t w_2'^t\big)$;

(iii) $\tilde{Y}_1 / \tilde{Y}_2 = \big(w_1^v / w_2^t, w_1^u / w_2^u, w_1^t / w_2^v; w_1'^v / w_2'^t, w_1^u / w_2^u, w_1'^t / w_2'^v\big)$;

(iv) $\tilde{Y}_1 - \tilde{Y} = \big(w_1^v - w_2^t, w_1^u - w_2^u, w_1^t - w_2^v; w_1'^v - w_2'^t, w_1^u - w_2^u, w_1'^t - w_2'^v\big)$;

(v) $p \times \tilde{Y}_1 = \big(p \times w_1^v, p \times w_1^u, p \times w_1^t; p \times w_1'^v, p \times w_1^u, p \times w_1'^t\big), \quad p \in R^+$.

2.2. *Preliminary of Single Valued Neutrosophic Set (SVNS)*

Smarandache (1998) laid the foundation for Neutrosophic Sets in 1998, which was later built upon by Wang *et al.* (2010) with the introduction of Single-Valued Neutrosophic Sets (SVNS). This concept aimed to address situations marked by uncertainty and incomplete data.

The following definition outlines an SVNS Θ defined over a specified set G:

$$\Theta = \{(n, P_m(n), Q_m(n), S_m(n)) : n \in G\},$$

where $P_m : R \to \{0, 1\} \cup (0, 1)$, $Q_m : R \to \{0, 1\} \cup (0, 1)$, $S_m : R \to \{0, 1\} \cup (0, 1)$ and so $0 \leqslant P_m(n) + Q_m(n) + S_m(n) \leqslant 3$. If an SVNS Θ over a given set G, we refer to the triplet $(P_m(n), Q_m(n), S_m(n))$ as a Single-Valued Neutrosophic Number (SVNN).

Mandal and Basu (2019) proposed a new scoring function designed to tackle Multiple Attribute Decision Making (MADM) challenges within the SVNS framework. The scoring process involves the following steps:

(i) Consider a three-dimensional space with the origin represented as Γ. Within this space, let denote a specific point $\Pi = (i_\theta, j_\theta, k_\theta)$, referred to as an SVNN. Perform a translation of this point into Π to arrive at $\Delta = (i_\varpi, j_\varpi, k_\varpi)$. Here $i_\varpi = i_\theta + \zeta$, $j_\varpi = j_\theta + \zeta$, $k_\varpi = k_\theta + \zeta$, where $\zeta > 0$, each representing k_ϖ, a real number that remains distinct and unchanging throughout the specific problem, play a crucial role. Now, let's consider another point, $\Delta^{/} = (i_\varpi, -j_\varpi, -k_\varpi)$, resulting from reflecting $\Lambda = (i_\varpi, j_\varpi, k_\varpi)$ across the *x-axis*, acting as a mirror.

(ii) Locate the score function $L_1(\Delta) = \cos\lambda$, with λ representing the angle between $O\Delta$ and $O\Delta^{/}$, and O denoting the origin.

(iii) If the score values for two distinct SVNNs, $\Delta_1 = (i_{\varpi_1}, j_{\varpi_1}, k_{\varpi_1})$ and $\Delta_2 = (i_{\varpi_2}, j_{\varpi_2}, k_{\varpi_2})$, denoted as $L_1(\Delta_1)$ and $L_1(\Delta_2)$, respectively, are equal, determine $\Delta_1^{**} = (i_{\varpi_1}, -j_{\varpi_1}, -\sqrt{k_{\varpi_1}})$ and $\Delta_2^{**} = (i_{\varpi_2}, -j_{\varpi_2}, -\sqrt{k_{\varpi_2}})$, respectively, for the corresponding translated points $\Delta_1^{*} = (i_{\varpi_1^*}, j_{\varpi_1^*}, k_{\varpi_1^*})$ and $\Delta_2^{*} = (i_{\varpi_2^*}, j_{\varpi_2^*}, k_{\varpi_2^*})$ where, $i_{\varpi_1^*} = i_{\varpi_1} + \zeta$, $j_{\varpi_1^*} = j_{\varpi_1} + \zeta$, $k_{\varpi_1^*} = k_{\varpi_1} + \zeta$ and $i_{\varpi_2^*} = i_{\varpi_2} + \zeta$, $j_{\varpi_2^*} = j_{\varpi_2} + \zeta$, $k_{\varpi_2^*} = k_{\varpi_2} + \zeta$.

(iv) Determine $\cos\varphi$ and $\cos\gamma$, where φ represents the angle between $O\Delta_1^*$ and $O\Delta_1^{**}$, and γ signifies the angle between $O\Delta_2^*$ and $O\Delta_2^{**}$, with Γ denoting the origin.

(v) The score mapping $L_2(\Delta_1) = \cos\varphi$, as well as $L_2(\Delta_2) = \cos\gamma$.

3. OPA-IF- Neutrosophic-TOPSIS Strategy under SVNS Environment Approach

The OPA-IF-Neutrosophic-TOPSIS Strategy within the SVNS Environment involves two primary phases. Initially, the OPA-IF technique is utilized to ascertain the weight or priority value (PV) of criteria. Subsequently, in the second phase, the Neutrosophic-TOPSIS Strategy under the SVNS Environment is applied to determine the ranking of alternatives. Figure 2 illustrates the computational steps involved in this approach.

3.1. *Phase-I: Intuitionistic Fuzzy Ordinal Priority Approach (OPA-IF)*

The process of obtaining attribute weights in the OPA-IF model involves solving the linear optimization model (1) (refer to equation (1)) for attributes in the following way:

Step-1: Let $E = \{\lambda_e : e = 1(1)f\}$ be the set of experts and $C = \{\phi_a : a = 1(1)b\}$ be the set of Attributes. The profit function is denoted by $\tilde{\zeta}$, also the decision variable $\tilde{\delta}_{ea}^{r}$

Table 1
Fuzzy ranks for attributes.

Linguistic variable	Intuitionistic triangular fuzzy set	Defuzzification
Bottom rank	(6, 7, 8; 5, 7, 9)	**7**
Bottom-to-middle rank	(5, 6, 7; 4, 6, 8)	6
Bottom-to-middle middle rank	(4, 5, 6; 3, 5, 7)	5
Middle rank	(3, 4, 5; 2, 4, 6)	4
Middle-to-top middle rank	(2, 3, 4; 1, 3, 5)	3
Middle-to-top rank	(1, 2, 3; 1, 2, 4)	2.25
Top rank	(1, 1, 1; 1, 1, 1)	1

denote fuzzy weight of ath. Attributes by eth expert at rth rank. $\tilde{\Re}^r_{ea}$ denote the linguistic-based measures of significance of ath Attributes by eth expert at rth rank from the Table 1. Equation (1) presents the mathematical model in a linear form.

$$\left.\begin{array}{ll} \text{Max}\,\tilde{\zeta} & \\ \text{Subject to } \tilde{\Re}^r_{ea}(\tilde{\delta}^r_{ea} - \tilde{\delta}^{r+1}_{ea}) \geqslant \zeta, & \forall e, a, \gamma \\ \tilde{\Re}^r_{ea}\tilde{\delta}^{\rho}_{ea} \geqslant \tilde{\xi}, & \forall e, a \\ \sum_{e=1}^{f}\sum_{a=1}^{\rho}\tilde{\delta}_{ea} = (1, 1, 1; 1, 1, 1), & \\ \delta^{/v}_{ea} \leqslant \delta^{v}_{ea} \leqslant \delta^{u}_{ea} = \delta^{/u}_{ea} \leqslant \delta^{t}_{ea} \leqslant \delta^{/t}_{ea}, & \forall e, a \\ \delta^{/v}_{ea} \geqslant 0, & \forall e, a \end{array}\right\} \tag{1}$$

Step-2: Once the optimization problem outlined in equation (1) has been addressed, the ranking can be computed using an appropriate defuzzification formula as described in equation (2).

$$W_a = \left[\frac{(\delta^v_a + 2\delta^u_a + \delta^t_a) + (\delta^{/v}_a + 2\delta^{/u}_a + \delta^{/t}_a)}{8}\right], \quad \forall a, \tag{2}$$

where $(\delta^v_a, \delta^u_a, \delta^t_a; \delta^{/v}_a, \delta^{/u}_a, \delta^{/t}_a)$ represents the optimal fuzzy weight of ath Attributes.

3.2. *Phase-II: Neutrosophic-Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) Strategy under SVNS Environment*

Consider the set of alternative $B = \{\varepsilon_d : d = 1(1)\lambda\}$, $d \geqslant 1$ and $C = \{\phi_a : a = 1(1)b\}$, $a \geqslant 2$ be the set of attributes with weights $w(\alpha^*_a)$, $a = 1(1)b$, respectively.

Decision-makers assign ratings to the ε_d, $d = 1(1)\lambda$ alternatives based on the attributes ϕ_a, $a = 1(1)b$, which are represented using an SVNN. Let's assume the rating for the ath attribute concerning the dth alternative is presented as follows:

$$\varepsilon^*_d = \big(\kappa_a, O_{\varepsilon_\kappa}(\phi_a), Q_{\varepsilon_\kappa}(\phi_a), S_{\varepsilon_\kappa}(\phi_a)\big), \quad d = 1(1)\lambda,$$

where $0 \leqslant O_{\varepsilon_\kappa}(Z_\varphi) + Q_{\varepsilon_\kappa}(Z_\phi) + S_{\varepsilon_\kappa}(Z_\varphi) \leqslant 3$. Here, (O_{da}, Q_{da}, S_{da}) is denoted as an SVNN. ε^*_{da}, $(d = 1(1)\lambda$ and $a = 1(1)b)$, where a represents the number of attributes and d represents the number of alternatives. The decision matrix is determined based on the ratings as, $\Phi^* = [\varepsilon^*_{da}]_{\lambda\times\delta}$.

The TOPSIS method is encapsulated in the following manner:

Step 1: The score-matrix $\Phi = [\varepsilon_{da}]_{\lambda\times\delta}$, $(d = 1(1)\lambda$ and $a = 1(1)b)$is acquired from the decision matrix $\Phi^* = [\varepsilon^*_{da}]_{\lambda\times\delta}$ utilizing the following described in preliminary section: i.e. $\varepsilon_{da} = L_1([\varepsilon^*_{da}]_{\lambda\times\delta})$.

Step 2: Determination of normalized decision matrix $F = [\tau_{da}]_{\lambda\times\delta}$, where,

$$\tau_{da} = \frac{\varepsilon_{da}}{\sqrt{\sum_{a=1}^{b} \varepsilon_{da}}}, \quad d = 1(1)\lambda. \tag{3}$$

Step 3: Calculation of the weighted normalized decision matrix $\Psi = [\upsilon_{da}]_{\lambda\times\delta}$, where, $\upsilon_{da} = w(\tilde{\alpha}^*_a)\lambda_{da}$, $d = 1(1)\lambda$ and $a = 1(1)b$.

Step 4: Determination of the Neutrosophic Positive Ideal Solution (NPIS) and Neutrosophic Negative Ideal Solution (NNIS), denoted by μ^+ and μ^-, respectively,

$$\mu^+ = \{\upsilon_1^+, \upsilon_2^+, \ldots, \upsilon_n^+\}, \quad \text{where } \upsilon_\theta^+ = \max_\theta \upsilon_{d\theta},\ \theta = 1(1)n,$$
$$\mu^- = \{\upsilon_1^-, \upsilon_2^-, \ldots, \upsilon_n^-\}, \quad \text{where } \upsilon_\theta^- = \max_\theta \upsilon_{d\theta},\ \theta = 1(1)n.$$

Step 5: Computation of the distance of each alternative from both the NPIS and NNIS using the equations (4) and (5) provided below:

$$\eth_d^+ = \sqrt{\sum_{\theta=1}^{\delta} (\upsilon_{d\theta} - \mu^+)^2}, \quad d = 1(1)\lambda, \tag{4}$$
$$\eth_d^- = \sqrt{\sum_{\theta=1}^{\delta} (\upsilon_{d\theta} - \mu^-)^2}, \quad d = 1(1)\lambda. \tag{5}$$

Step 6: Evaluation of the performance score for each alternative using the equation (6):

$$\wp_d = \eth_d^- / (\eth_d^+ + \hbar_d^-), \quad d = 1(1)\lambda. \tag{6}$$

Step 7: Arrangement of the alternatives based on their performance scores, with the alternative having the highest score receiving the top ranking, and the one with the lowest score being allocated the lowest ranking.

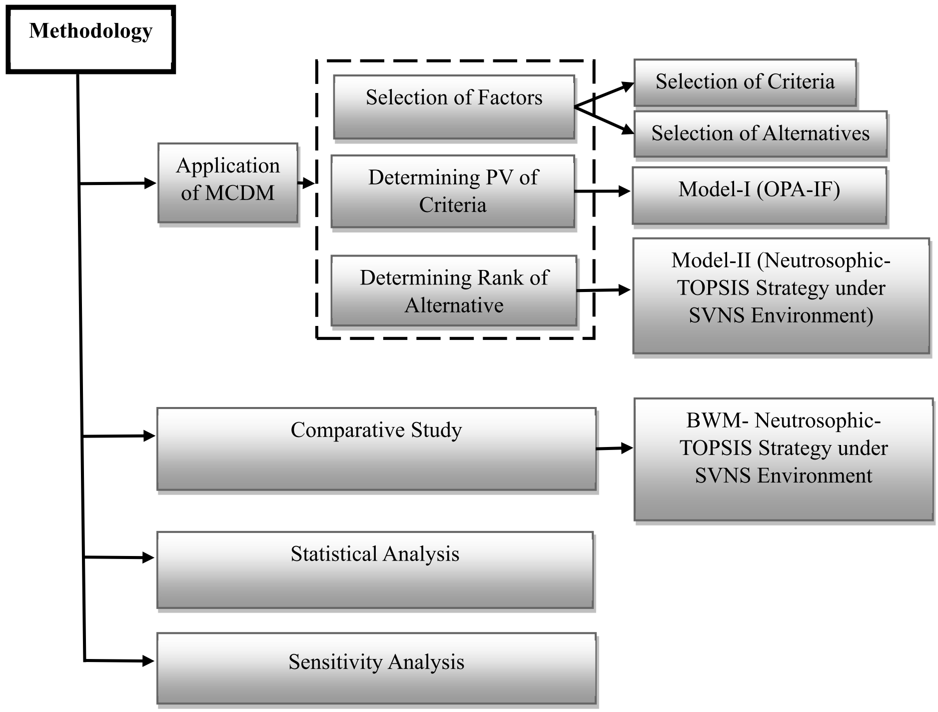

Fig. 2. Schematic diagram of methodology.

4. Detailed Methodology

This study aims to identify the key indicators necessary for conducting an efficiency analysis using a new fuzzy-based Multiple Criteria Decision Making (MCDM) approach. The methodology consists of two main stages: the execution of MCDM and the validation of the model. The outlined procedure is visually depicted in Fig. 2.

4.1. *Implementation of MCDM*

The objective of the upcoming section is to assess the priority values (PV) of both criteria and alternatives. This phase entails three key components: identifying factors, employing OPA-IF, and utilizing the Neutrosophic-TOPSIS strategy within the SVNS environment. The decision hierarchy for the matter is illustrated in Fig. 3.

Step-1: Selection of Factors:

A comprehensive examination of pertinent literature is conducted to select criteria and alternatives, followed by assembling a panel comprising specialists and stakeholders. Table 2 and 3 presents all the identified criteria and alternatives being investigated.

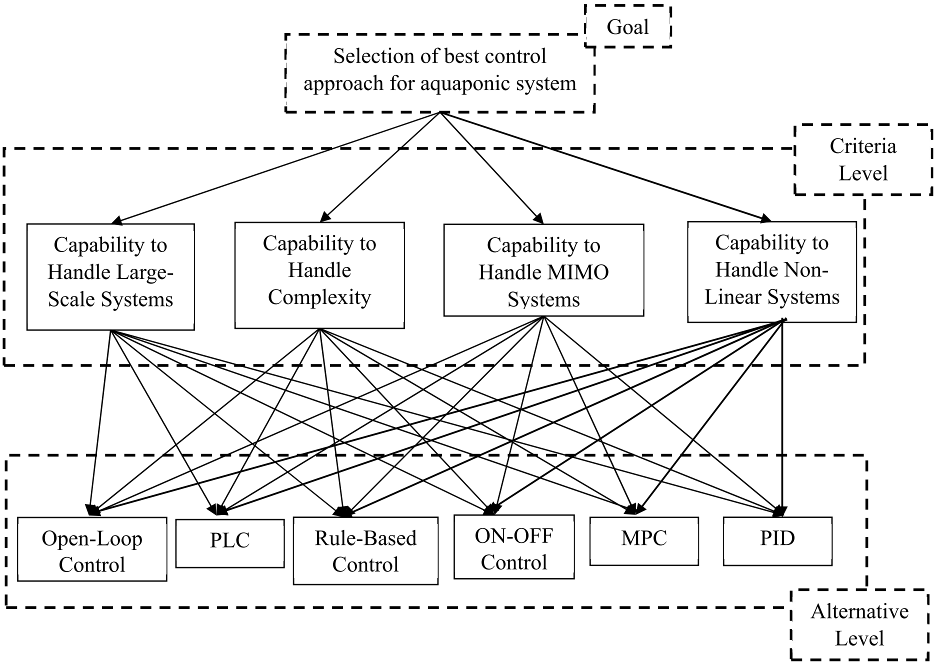

Fig. 3. Hierarchical structure of the decision-making problem.

Table 2
The selected criteria for the consideration of this study.

Name of the criteria	Description of criteria
Capability to handle large-scale systems (ϕ_1)	The large-scale adoption of aquaponic systems signifies a substantial progression in sustainable agriculture, catering to commercial and industrial-scale production demands. This transition offers myriad advantages over conventional farming methods, presenting a promising solution to global issues such as food security, environmental sustainability, and economic development (Sethupathi *et al.*, 2019).
Capability to handle complexity (ϕ_2)	There are several factors that contribute to the complexity associated to the aquaponic system, such as interconnected system dynamics, multivariate nature, nonlinear relationships, uncertainty and variability, and many more (Keesman *et al.*, 2019).
Capability to handle multi-input multi-output (MIMO) system (ϕ_3)	Aquaponic systems involve multiple variables and parameters that influence system performance, including water quality, temperature, pH, nutrient levels, stocking density, and plant growth. Managing and optimizing these variables simultaneously requires a sophisticated control approach capable of handling multivariate interactions (Keesman *et al.*, 2019).
Capability to handle Non-linear system (ϕ_4)	The relationships between input variables and system outputs in aquaponic systems are often nonlinear and may exhibit complex behaviours. Traditional linear control methods may be inadequate for capturing these nonlinear dynamics, necessitating the use of advanced control techniques (Keesman *et al.*, 2019).

Table 3
The selected alternatives for the consideration of this study.

Name of the alternative	Description of alternative
Open-loop control strategy (ε_1)	Open-loop control is a method where the control action is predetermined based on a set of inputs without considering the system's actual output. This approach doesn't involve feedback or adjustments based on the system's response. Instead, it relies solely on the initial input commands. While simple and easy to implement, open-loop control doesn't account for external disturbances or changes in the system, making it less adaptable and potentially less accurate than closed-loop control methods (Bequette, 2003).
Programmable logic control (PLC) (ε_2)	Programmable Logic Control (PLC) is a specialized form of control system widely used in industrial automation applications. PLCs are designed to control machinery and processes by executing a sequence of logic-based commands, known as ladder logic, based on input signals from sensors and user-defined programming. PLCs are versatile and powerful control systems widely used in various industries, including manufacturing, automotive, energy, and process control, to automate and optimize industrial processes (Wei, 2010).
Rule-based control strategy (ε_3)	A rule-based control strategy, also known as heuristic or knowledge-based control or fuzzy logic control, relies on a set of predefined rules or decision-making criteria to determine the control actions. These rules are typically established by experts or based on empirical knowledge of the system behaviour. In a rule-based control system, the controller evaluates the current state of the system and applies the rules to determine the appropriate control action (Moudgal *et al.*, 1994).
On-Off control strategy (ε_4)	On-off control, also known as binary control, is a simple form of control system where the control action is either fully on or fully off based on a predefined setpoint or threshold. In this method, the controller activates the control device (such as a pump or heater) when the system variable crosses a predetermined threshold or setpoint, and deactivates it when the variable returns within a specified range. On-off control is commonly used in applications where precise control is not necessary, and where the system response is relatively slow or non-critical. While straightforward and cost-effective, on-off control can lead to oscillations around the setpoint and may not provide optimal control in systems with significant external disturbances or nonlinear dynamics (Haber *et al.*, 2012).
MPC strategy (ε_5)	Model Predictive Control (MPC) is an advanced control strategy used in a wide range of industrial processes and systems to optimize system performance while considering constraints and predictive models of the process dynamics. Unlike traditional control methods that rely on a fixed control law, MPC utilizes a dynamic optimization approach to predict future system behaviour and compute optimal control actions over a finite time horizon. MPC finds applications in diverse industries, including chemical process control, power systems, automotive systems, robotics, and building HVAC (Heating, Ventilation, and Air Conditioning) systems, where precise control, optimization, and constraint handling are critical for efficient operation (Balaji and Maheswari, 2012).
PID control strategy (ε_6)	PID control, short for Proportional-Integral-Derivative control, is a widely used feedback control strategy employed in various industrial processes and systems to achieve desired performance objectives. It operates based on the error signal, which represents the difference between the desired setpoint and the measured process variable. PID control finds widespread application in various industrial processes, including temperature control, pressure regulation, speed control, level control, and flow control, due to its simplicity, effectiveness, and versatility (Sung *et al.*, 2009).

Step-2: Application of OPA-IF (Model-I):

In the present study, opinions from three experts were taken. Based on these expert opinions, Capability to Handle MIMO Systems (ϕ_3) and Capability to Handle Complexity (ϕ_2) were identified as being more highly and moderately highly responsible for efficiency, profitability, and sustainability of aquaponic systems, respectively; while Capability to Handle Large-Scale Systems (ϕ_1) and Capability to Handle Non-Linear Systems (ϕ_4) were categorized as having high and medium responsibility, respectively. It was clearly indicated by the experts that for Capability to Handle MIMO Systems and all other criteria, higher values are preferable. The fuzzy priority value of criteria can be determined using OPA-IF. Fuzzy weights for attributes can be estimated using equation (7).

$$
\begin{aligned}
&\text{Max}\tilde{\zeta}\\
&\left.\begin{aligned}
\text{Subject to } & (6,7,8;5,7,9)(\tilde{\delta}_3-\tilde{\delta}_1)\geqslant\tilde{\xi}\\
& (4,5,6;3,5,7)(\tilde{\delta}_1-\tilde{\delta}_4)\geqslant\tilde{\xi}\\
& (2,3,4;1,3,5)(\tilde{\delta}_4-\tilde{\delta}_2)\geqslant\tilde{\xi}\\
& (1,1,1;1,1,1)\tilde{\delta}_2\geqslant\tilde{\xi}\\
& \tilde{\delta}_1+\tilde{\delta}_2+\tilde{\delta}_3+\tilde{\delta}_4=(1,1,1;1,1,1)\\
& \delta_i^{/v}\leqslant\delta_i^{v}\leqslant\delta_i^{u}=\delta_i^{/u}\leqslant\delta_i^{t}\leqslant\delta_i^{/t}, \qquad \forall i=1(1)4\\
& \delta_i^{/v}\geqslant 0, \qquad \forall i=1(1)4
\end{aligned}\right\}
\end{aligned}
\tag{7}
$$

Step 3: Neutrosophic-TOPSIS Strategy under SVNS Environment (Model II): The decision maker utilizes SVNNs to assess alternatives according to their attributes, leading to the generation of Decision Matrix as Matrix-1.

Matrix-1: Decision Matrix:

$$
\Phi = \begin{array}{c} \\ \varepsilon_1\\ \varepsilon_2\\ \varepsilon_3\\ \varepsilon_4\\ \varepsilon_5\\ \varepsilon_6 \end{array}
\begin{array}{c}
\begin{array}{cccc} \phi_1 & \phi_2 & \phi_3 & \phi_4 \end{array}\\
\begin{bmatrix}
(0.9,0.7,0.5) & (0.7,0.5,0.4) & (0.7,0.5,0.4) & (1,0.5,0.6)\\
(0.5,0.3,0.4) & (0.8,0.6,0.4) & (0.7,0.4,0.2) & (1,0.4,0.2)\\
(0.8,0.5,0.6) & (1,0.5,0.4) & (0.9,0.8,0.6) & (0.9,0.4,0.2)\\
(0.6,0.5,0.2) & (1,0.4,0.3) & (0.8,0.7,0.4) & (0.5,0.2,0.1)\\
(0.7,0.4,0.3) & (0.8,0.7,0.6) & (0.9,0.5,0.2) & (0.7,0.5,0.2)\\
(0.8,0.6,0.4) & (0.9,0.5,0.3) & (0.8,0.6,0.1) & (0.9,0.4,0.3)
\end{bmatrix}
\end{array}.
$$

Matrix Φ is derived by shifting the values of each entry. Each entry in Matrix Φ is incremented by 0.01 across all components, thereby producing Matrix-2.

Matrix-2: Translation of Φ:

$$\begin{array}{c} \\ \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \\ \varepsilon_6 \end{array} \begin{array}{c} \begin{array}{cccc} \qquad\phi_1\qquad & \qquad\phi_2\qquad & \qquad\phi_3\qquad & \qquad\phi_4\qquad \end{array} \\ \begin{bmatrix} (0.91, 0.71, 0.51) & (0.71, 0.51, 0.41) & (0.71, 0.51, 0.41) & (1.01, 0.51, 0.61) \\ (0.51, 0.31, 0.41) & (0.81, 0.61, 0.41) & (0.71, 0.41, 0.21) & (1.01, 0.41, 0.21) \\ (0.81, 0.51, 0.61) & (1.01, 0.51, 0.41) & (0.91, 0.81, 0.61) & (0.91, 0.41, 0.21) \\ (0.61, 0.51, 0.21) & (1.01, 0.41, 0.31) & (0.81, 0.71, 0.41) & (0.51, 0.21, 0.11) \\ (0.71, 0.41, 0.31) & (0.81, 0.71, 0.61) & (0.91, 0.51, 0.21) & (0.71, 0.51, 0.21) \\ (0.81, 0.61, 0.41) & (0.91, 0.51, 0.31) & (0.81, 0.61, 0.11) & (0.91, 0.41, 0.31) \end{bmatrix} \end{array}.$$

The next step involves generating the score matrix using the score function. Matrix-3 represents the score matrix denoted as Φ^*. The score value is given by,

$$\begin{aligned} L_1(0.91, 0.71, 0.51) &= \frac{0.91 \times 0.91 + 0.71 \times (-0.71) + 0.51 \times (-0.51)}{\sqrt{0.91^2 + 0.71^2 + 0.51^2}\sqrt{0.91^2 + (-0.71)^2 + (-0.51)^2}} \\ &= 0.04013. \end{aligned}$$

Matrix-3: Score Matrix:

$$\Phi^* = \begin{array}{c} \\ \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \\ \varepsilon_6 \end{array} \begin{array}{c} \begin{array}{cccc} \quad\phi_1\quad & \quad\phi_2\quad & \quad\phi_3\quad & \quad\phi_4\quad \end{array} \\ \begin{bmatrix} 0.04013 & 0.081411 & 0.081411 & 0.234763 \\ -0.007819 & 0.096882 & 0.40751 & 0.655603 \\ 0.018551 & 0.408686 & -0.107795 & 0.59204 \\ 0.100399 & 0.588569 & -0.01212 & 0.644641 \\ 0.312247 & -0.14364 & 0.462686 & 0.247309 \\ 0.096882 & 0.398463 & 0.261366 & 0.51625 \end{bmatrix} \end{array}.$$

The Normalized Decision Matrix is determined by using equation (4) on matrix Φ^*. As shown in Matrix-4, the Normalized Decision Matrix is denoted by F.

$$\begin{aligned} \tau_{11} &= \frac{0.04013}{\sqrt{0.04013^2 + (-0.007819)^2 + 0.018551^2 + 0.100399^2 + 0.312247^2 + 0.096882^2}} \\ &= 0.116342. \end{aligned}$$

Matrix-4: Decision Matrix with Normalization:

$$F = \begin{array}{c} \\ \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \\ \varepsilon_6 \end{array} \begin{array}{c} \begin{array}{cccc} \quad\phi_1\quad & \quad\phi_2\quad & \quad\phi_3\quad & \quad\phi_4\quad \end{array} \\ \begin{bmatrix} 0.116342 & 0.096695 & 0.11915 & 0.186845 \\ -0.02267 & 0.11507 & 0.596416 & 0.521787 \\ 0.053782 & 0.485411 & -0.157764 & 0.471199 \\ 0.291066 & 0.699066 & -0.017739 & 0.513063 \\ 0.905234 & -0.170606 & 0.677169 & 0.19683 \\ 0.280869 & 0.473269 & 0.382526 & 0.410878 \end{bmatrix} \end{array}.$$

Once the criteria crisp weights are determined by solving the equation (7), the weighted normalized decision matrix is computed. This process entails multiplying each criteria weight by the corresponding element in its respective row of Matrix. Denoted as matrix Ψ, it is illustrated by Matrix-5.

Matrix-5: Weighted Normalized Decision Matrix:

$$\Psi = \begin{array}{c} \\ \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \\ \varepsilon_6 \end{array} \begin{array}{c} \begin{array}{cccc} \phi_1 & \phi_2 & \phi_3 & \phi_4 \end{array} \\ \begin{bmatrix} 0.116342 \times 0.27972 & 0.096695 \times 0.195804 & 0.11915 \times 0.286713 & 0.186845 \times 0.237762 \\ -0.02267 \times 0.27972 & 0.11507 \times 0.195804 & 0.596416 \times 0.286713 & 0.521787 \times 0.237762 \\ 0.053782 \times 0.27972 & 0.485411 \times 0.195804 & -0.157764 \times 0.286713 & 0.471199 \times 0.237762 \\ 0.291066 \times 0.27972 & 0.699066 \times 0.195804 & -0.017739 \times 0.286713 & 0.513063 \times 0.237762 \\ 0.905234 \times 0.27972 & -0.170606 \times 0.195804 & 0.677169 \times 0.286713 & 0.19683 \times 0.237762 \\ 0.280869 \times 0.27972 & 0.473269 \times 0.195804 & 0.382526 \times 0.286713 & 0.410878 \times 0.237762 \end{bmatrix} \end{array}.$$

$$= \begin{array}{c} \\ \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \\ \varepsilon_6 \end{array} \begin{array}{c} \begin{array}{cccc} \phi_1 & \phi_2 & \phi_3 & \phi_4 \end{array} \\ \begin{bmatrix} 0.032543316 & 0.018933394 & 0.034162112 & 0.044424922 \\ -0.006341469 & 0.022531272 & 0.171000649 & 0.12406148 \\ 0.015044118 & 0.095045638 & -0.045233224 & 0.112033371 \\ 0.081417212 & 0.136880078 & -0.00508614 & 0.121987079 \\ 0.253212567 & -0.03340555 & 0.194153626 & 0.04679894 \\ 0.078565011 & 0.092668179 & 0.109675399 & 0.097691315 \end{bmatrix} \end{array}.$$

Subsequently, ascertain NPIS and NNIS using the formulas $\upsilon_\theta^+ = \max_\theta \upsilon_{d\theta}, \theta = 1(1)6$ and $\upsilon_\theta^- = \min_\theta \upsilon_{d\theta}, \theta = 1(1)6$ values, respectively.

$$\begin{aligned} \upsilon_1^- &= \min\{0.032543316, -0.006341469, 0.015044118, 0.081417212, \\ &\qquad 0.253212567, 0.078565011\} \\ &= -0.006341469. \end{aligned}$$

So,

$$\begin{aligned} \mu^+ &= \{\upsilon_1^+, \upsilon_2^+, \upsilon_3^+, \upsilon_4^+\} = \{0.253212567, 0.136880078, 0.194153626, 0.12406148\}, \\ \mu^- &= \left\{\upsilon_1^-, \upsilon_2^-, \upsilon_3^-, \upsilon_4^-\right\} = \{-0.006341469, -0.03340555, -0.045233224, \\ &\qquad 0.044424922\}, \\ \tau_1^+ &= \max\{0.032543316, -0.006341469, 0.015044118, 0.081417212, \\ &\qquad 0.253212567, 0.078565011\} \\ &= 0.253212567. \end{aligned}$$

Next, the distances between each alternative using the NPIS and NNIS are computed using the equations (4) and (5), respectively. Table 4 displays the distances between alternatives

Table 4
NPIS and NNIS distances from each alternative.

	Value		Value
∂_1^+	0.30748269	∂_1^-	0.102737582
∂_2^+	0.284569864	∂_2^-	0.237124433
∂_3^+	0.340477708	∂_3^-	0.146724072
∂_4^+	0.263086358	∂_4^-	0.210538495
∂_5^+	0.186993837	∂_5^-	0.353100548
∂_6^+	0.200719748	∂_6^-	0.223467415

Table 5
Performance scores of alternative.

Alternatives	Performance scores	Rank
ε_1	$\wp_1 = 0.250445$	6
ε_2	$\wp_2 = 0.454528$	3
ε_3	$\wp_3 = 0.301157$	5
ε_4	$\wp_4 = 0.444526$	4
ε_5	$\wp_5 = 0.653776$	1
ε_6	$\wp_6 = 0.526813$	2

calculated using NPIS and NNIS.

$$\begin{aligned}
\partial_1^+ &= \sqrt{(\upsilon_{11} - \mu_1^+)^2 + (\upsilon_{12} - \mu_2^+)^2 + (\upsilon_{13} - \mu_3^+)^2 + (\upsilon_{14} - \mu_4^+)^2} \\
&= \sqrt{(0.032543316 - 0.253212567)^2 + (0.018933394 - 0.136880078)^2} \\
&\quad + \sqrt{(0.034162112 - 0.194153626)^2 + (0.044424922 - 0.12406148)^2} \\
&= 0.30748269, \\
\partial_1^- &= \sqrt{(\upsilon_{11} - \mu_1^-)^2 + (\upsilon_{12} - \mu_2^-)^2 + (\upsilon_{13} - \mu_3^-)^2 + (\upsilon_{14} - \mu_4^-)^2} \\
&= \sqrt{(0.032543316 - (-0.006341469))^2 + (0.018933394 - (-0.03340555))^2} \\
&\quad + \sqrt{(0.034162112 - (-0.045233224))^2 + (0.044424922 - 0.044424922)^2} \\
&= 0.102737582.
\end{aligned}$$

The performance score of each alternative is computed using equation (6). Table 5 presents the performance scores for all alternatives. Arrange the alternatives in ascending order according to their performance scores and assign ranks accordingly.

$$\wp_1 = \partial_1^- / \left(\partial_1^+ + \partial_1^-\right) = 0.102737582/(0.30748269 + 0.102737582) = 0.250445.$$

4.2. *Result from Comparative Study*

Experts have been consulted to identify the vectors appropriate for utilization in the BWM-Neutrosophic-TOPSIS Strategy under SVNS Environment, along with determining the

Table 6
Comparison of best criteria with other criteria.

	ϕ_1	ϕ_2	ϕ_3	ϕ_4
ϕ_3 (best criteria)	2	4	1	3

Table 7
To the worst criteria, there are other criteria.

	ϕ_2 (worst criteria)
ϕ_1	3
ϕ_2	1
ϕ_3	4
ϕ_4	2

most and least significant aspects. Through expert consensus, it has been established that ϕ_3 holds the highest significance, while ϕ_2 is deemed to be the least significant criterion. The best-to-others vector is presented in Table 6, and the worst-to-others vector is outlined in Table 7.

The nonlinear mathematical model (8) (refer to equation (8)) can also be used to determine the weight of each criterion.

$$\begin{aligned}
&\min \hbar \\
&\text{s.t.} \left|\frac{D_3}{D_1} - 2\right| < \hbar, \\
&\quad \left|\frac{D_3}{D_2} - 4\right| < \hbar, \\
&\quad \left|\frac{D_3}{D_4} - 3\right| < \hbar, \\
&\quad \left|\frac{D_1}{D_2} - 4\right| < \hbar, \\
&\quad \left|\frac{D_1}{D_2} - 3\right| < \hbar, \\
&\quad \left|\frac{D_3}{D_2} - 4\right| < \hbar, \\
&\quad \left|\frac{D_4}{D_2} - 2\right| < \hbar, \\
&\quad \sum_{j=1}^{4} D_j = 1, \\
&\quad D_j \geqslant 0, \quad \text{for all } j = 1(1)4.
\end{aligned} \tag{8}$$

Utilizing the equation (3) on matrix Φ^*, the Normalized Decision Matrix can be determined. As shown in Matrix-6, the Normalized Decision Matrix decision matrix is denoted by F.

Matrix-6: Normalized Decision Matrix:

$$F = \begin{array}{c} \\ \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \\ \varepsilon_6 \end{array} \begin{array}{c} \begin{array}{cccc} \phi_1 & \phi_2 & \phi_3 & \phi_4 \end{array} \\ \begin{bmatrix} 0.116342355 & 0.096695548 & 0.119150779 & 0.186845995 \\ -0.02267075 & 0.115070426 & 0.596416897 & 0.521787988 \\ 0.053782722 & 0.485411653 & -0.157764658 & 0.471199176 \\ 0.291066534 & 0.699066115 & -0.017739464 & 0.513063301 \\ 0.905234929 & -0.170606915 & 0.677169964 & 0.196830834 \\ 0.280869914 & 0.47326963 & 0.382526392 & 0.41087818 \end{bmatrix} \end{array}.$$

Once the criteria weights are determined by the equation (8), the subsequent step involves computing the weighted normalized decision matrix. This matrix is generated by multiplying each criterion weight by the corresponding element in the respective row of the associated matrix F. The resultant weighted normalized decision matrix (Matrix-7) is represented by matrix Ψ.

Matrix-7: Weighted Normalized Decision Matrix:

$$\Psi = \begin{array}{c} \\ \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \\ \varepsilon_4 \\ \varepsilon_5 \\ \varepsilon_6 \end{array} \begin{array}{c} \begin{array}{cccc} \phi_1 & \phi_2 & \phi_3 & \phi_4 \end{array} \\ \begin{bmatrix} 0.03008854 & 0.010002988 & 0.055466742 & 0.032214827 \\ -0.005863125 & 0.011903837 & 0.277642349 & 0.089963446 \\ 0.013909325 & 0.050214999 & -0.073442168 & 0.081241237 \\ 0.075275828 & 0.072317184 & -0.008258026 & 0.08845919 \\ 0.234112482 & -0.017648991 & 0.315234293 & 0.033936351 \\ 0.072638771 & 0.048958927 & 0.178072631 & 0.070841065 \end{bmatrix} \end{array}.$$

Next step is to identify NPIS and NNIS using the formulas $\upsilon_\theta^+ = \max_\theta \upsilon_{d\theta}, \theta = 1(1)6$ and $\upsilon_\theta^- = \min_\theta \upsilon_{d\theta}, \theta = 1(1)6$ values, respectively.

So,

$$\begin{aligned} \mu^+ &= \{\upsilon_1^+, \upsilon_2^+, \upsilon_3^+, \upsilon_4^+\} = \{0.234112482, 0.072317184, 0.315234293, 0.89963446\}, \\ \mu^- &= \left\{\upsilon_1^-, \upsilon_2^-, \upsilon_3^-, \upsilon_4^-\right\} \\ &= \{-0.005863125, -0.017648991, -0.073442168, 0.032214827\}. \end{aligned}$$

The distance of each alternative from both NPIS and NNIS is calculated using equations (4) and (5), respectively. Table 8 presents the distances for each alternative's weights from NPIS and NNIS.

The evaluation score for each option is calculated utilizing equation (6). Fig. 4 displays the performance scores for each alternative according to both the proposed method and the current method.

4.3. *Statistical Analysis*

The rankings produced by the two methods can be compared using the Spearman correlation coefficient, which measures the linear relationship between two variables. This

Table 8
Distances of each alternative between NPIS as well as NNIS.

	Value		Value
∂_1^+	0.341061448	∂_1^-	0.136655264
∂_2^+	0.250302254	∂_2^-	0.357027465
∂_3^+	0.447351546	∂_3^-	0.0860236
∂_4^+	0.360386773	∂_4^-	0.148626522
∂_5^+	0.105985604	∂_5^-	0.456793878
∂_6^+	0.214005501	∂_6^-	0.27450108

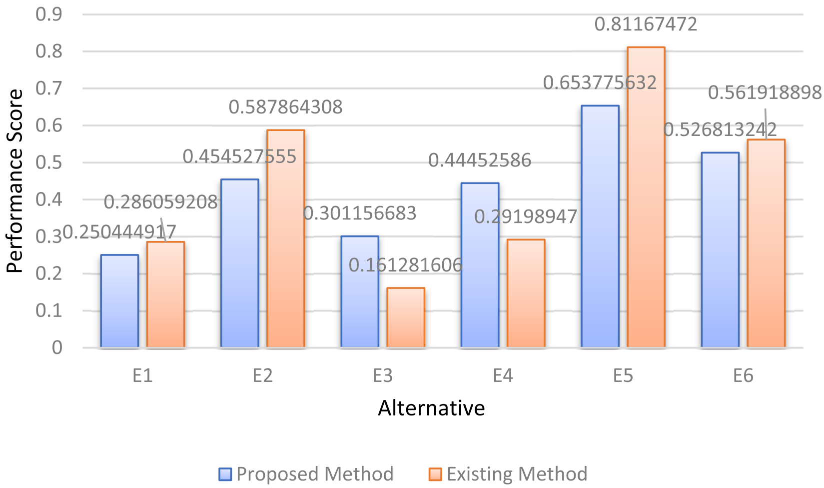

Fig. 4. Comparative study.

coefficient ranges from -1 to 1: -1 indicates no linear correlation, 0 signifies no linear correlation, and 1 indicates a perfect linear correlation. To evaluate the association between variables on interval scales, Pearson's correlation coefficient (Sedgwick, 2012) can be employed, as demonstrated in equation (9):

$$\chi(\varpi, \iota) = \frac{\operatorname{cov}(\varpi, \iota)}{\eta_\varpi \eta_\iota}. \tag{9}$$

σ, as well as ξ, is a covariant of $\operatorname{cov}(\sigma, \xi)$. SD is represented by σ, as well as ξ, in both η_σ, as well as η_ξ.

The Pearson correlation coefficient is important for assessing the absence of a perfect correlation between two variables when it deviates from a value of 1, as given in equation (10):

$$\begin{cases} F_0: & -\infty < \chi \leqslant 0, \\ F_1: & 0 < \chi < \infty. \end{cases} \tag{10}$$

Table 9
t-Test: Paired two sample for means.

	Proposed method (Variable 1)	Existing method (Variable 2)
Mean	0.438541	0.450131
Variance	0.021733	0.059509
Observations (ρ)	6	6
Pearson correlation	0.886954	
Hypothesized mean difference (α)	0	
Df	5	
t Stat	−0.21494	
P (T <= t) one-tail	0.419153	
t Critical one-tail	2.015048	
P (T <= t) two-tail	0.838306	
t Critical two-tail	2.570582	

Pearson correlation coefficient alongside Student's *t-distribution* with degrees of freedom $\lambdabar - 1$, is presented by equation (11).

$$t = \chi\left(\frac{\lambdabar - 2}{1 - \chi^2}\right)^{\frac{1}{2}}. \tag{11}$$

The null hypothesis should be rejected if t (equation (11)) suppresses $t_\alpha(\lambdabar - 2)$. The Pearson correlation coefficient χ falls within the range of $\lambdabar$.

Both methods generate rankings, which are then assessed using the Spearman correlation coefficient. If the rankings are identical, resulting in a Spearman correlation coefficient of 1, further hypothesis testing is unnecessary. However, if the rankings differ, a hypothesis test can be conducted to validate the Spearman correlation coefficients, as described in equation (9). To compare the proposed approach with the BWM-TOPSIS strategy under the SVNS environment weights, the analysis will employ the Pearson correlation coefficient, as specified in Table 9. It's worth noting that there is a noticeable correlation between the proposed PV models and the currently established PV models, as corroborated by Ataei *et al.* (2020). The analysis findings suggest that $t = \chi(\frac{\lambdabar-2}{1-\chi^2})^{\frac{1}{2}}$ should outperform $t_{0.05}(\lambdabar - 2)$. A hypothesis test is carried out to confirm a positive correlation between the attributes of the existing and proposed methods.

4.4. *Sensitivity Analysis*

The objective is to understand how changing the weight coefficients impacts various scenarios, each defined by a unique set of parameters. To achieve this, sensitivity analysis is utilized. This analytical method allows us to evaluate the primary criterion, as defined by equation (12), and to assess how sensitive the criterion PVs ($\mathbb{N}(\tilde{\mathrm{K}}_{\Re})$) are to changes in these coefficients. Furthermore, we delve into the progression of the leading criterion to

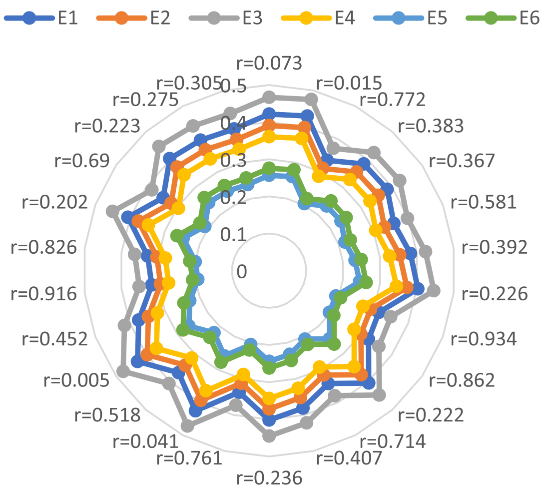

Fig. 5. Results of the sensitivity analysis for ∂_d^+.

gain insights into how it evolves over time or under different conditions.

$$\tilde{\mathrm{K}}'_{\Re} = \tilde{\mathrm{K}}_{\Re}\left(\frac{1 - r\tilde{\mathrm{K}}_{\varepsilon}}{1 - \tilde{\mathrm{K}}_{\varepsilon}}\right), \qquad \Re = 1(1)4. \tag{12}$$

When $\mathrm{K}'_{\Re}$ represents the initial value of the criterion, denoted $\tilde{\mathrm{K}}_{\Re}$ ($\Re = 1(1)\Xi$); $\tilde{\mathrm{K}}_{\varepsilon}$, it signifies the criterion's starting point. $r_{\Re} \in (0, 1) \cup \{0, 1\}$, on the other hand, represents the adjusted value.

For this study, 25 unique scenarios are generated using equation (12). In these scenarios, the variable r is capable of assuming random values between 0 and 1. Figures 5 and 6 depict the results of sensitivity analyses conducted separately for each alternative of ∂_d^+ and ∂_d^-. Figure 7 presents an overview of the sensitivity analysis results. Notably, according to Fig. 7, the "Model Predictive Control (MPC) strategy" emerges as the most sensitive parameter across all cases.

5. Conclusion

This research introduces a novel Multi-Criteria Decision-Making (MCDM) approach, termed the OPA-IF-Neutrosophic-TOPSIS hybrid technique under the SVNS Environment. Within this approach, the OPA-IF component evaluates the Priority Value (PV) of different attributes, while the Neutrosophic-TOPSIS strategy establishes rankings among alternative choices. The PV, determined by OPA-IF, plays a crucial role in calculating the Utility Functional Value of alternatives within the Neutrosophic-TOPSIS framework. This hybrid MCDM method aims to aid in selecting the most appropriate control approach for aquaponics systems. Notably, findings from the OPA-IF analysis underscore the importance of the 'Capability to Handle MIMO Systems' criterion, leading to the conclusion by

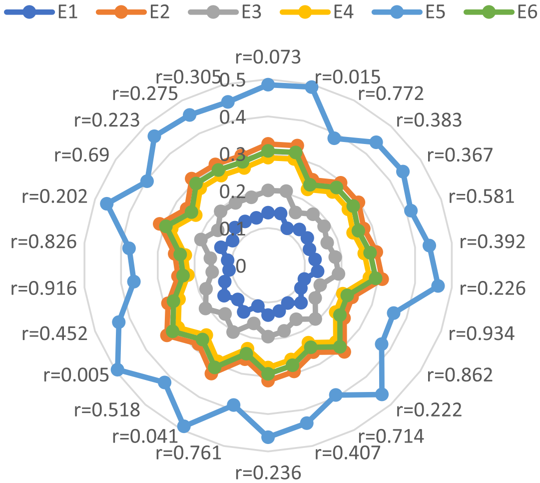

Fig. 6. Results of the sensitivity analysis for ∂_d^-.

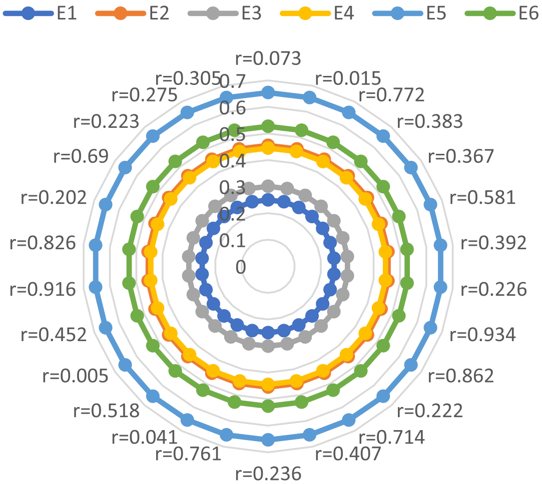

Fig. 7. The overview of the sensitivity analysis.

the Neutrosophic-TOPSIS strategy that 'Model Predictive Control (MPC)' is the optimal choice for large-scale aquaponic systems.

To verify the effectiveness of this proposed MCDM technique, its results are compared with the BWM-Neutrosophic-TOPSIS Strategy under the SVNS Environment. This comparison confirms the alignment of outcomes between the proposed model and existing methods, as demonstrated by a strong positive correlation determined through Pearson correlation analysis. Furthermore, a sensitivity analysis indicates that the MPC strategy is the most sensitive parameter within the proposed method.

Overall, this study makes a significant contribution to the scientific understanding of control strategies in aquaponics by providing a deeper insight into the various methodologies that can be applied to optimize system performance. Beyond advancing theoretical knowledge, it also offers valuable, actionable guidance for farmers, aquaponics practitioners, and stakeholders in the field. By identifying the most effective control approaches and highlighting their practical benefits, the research empowers practitioners to make more informed decisions when managing their aquaponic systems. Through these efforts, the study aims to contribute to the broader goal of promoting sustainable, efficient, and scalable food production systems for the future.

However, despite the numerous advantages of the proposed method, it is essential to recognize its inherent limitations. One of the primary challenges in implementing this technique lies in the substantial amount of data and expertise required to effectively apply the approach. The complexity of integrating various fuzzy logic and decision-making elements demands a high level of technical knowledge, which could pose difficulties for practitioners without specialized training or experience. Furthermore, while the study successfully addresses ranking within the context of a Neutrosophic environment, the method may face constraints when dealing with other extensions of fuzzy set theory, such as hesitant fuzzy sets or spherical fuzzy sets. These alternative frameworks introduce additional layers of complexity and may not be as easily accommodated within the current model, potentially limiting its applicability in certain scenarios. Another limitation stems from the reliance on expert assessments and opinions to establish rankings within the model. While expert judgment is a valuable tool, it is inherently subjective, which means that different experts may interpret the same data in varied ways. This subjectivity can lead to inconsistencies in the rankings and conclusions drawn from the model, as each expert may have differing perspectives or biases, introducing an element of uncertainty into the decision-making process.

Moving forward, this study will expand its scope in several key directions. First, a thorough investigation into the critical decision-making processes that guide the selection of the most appropriate control strategies for large-scale aquaponic systems will be undertaken. Second, the study will leverage a broader range of MCDM methodologies to assess and prioritize various control techniques. These methodologies will be applied to evaluate the performance and suitability of different control strategies based on their ability to manage Multiple Input Multiple Output (MIMO) systems, their capacity to address system non-linearities, and their effectiveness in large-scale, dynamic settings. Third, the research will be enriched by incorporating extensive data collection, analysis, and modelling efforts. This will not only deepen the understanding of aquaponic system dynamics but also result in practical, actionable recommendations for practitioners in the field. By bridging gaps in the existing body of knowledge, the study aims to contribute to improving the efficiency and sustainability of aquaponic food production, providing valuable insights that can be directly applied to real-world settings. Finally, the study will examine the sensitivity and robustness of the MCDM models used in the evaluation process. This will involve testing how well the selected models perform under varying conditions and uncertainties, ensuring their reliability and applicability in real-world aquaponic systems.

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