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A Neutrosophic Approach for Opponent Analysis and Game Strategy Formulation in College Volleyball

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Abstract: In competitive college volleyball, effective opponent analysis is crucial for strategic decision-making, particularly when facing teams with varying performance dynamics. This study introduces a Q-Neutrosophic Soft Set (QNSS) approach to opponent analysis, enabling multi-context decision evaluation based on a granular assessment of opponent characteristics across different game conditions. Our QNSS proposes a novel Context-wise Aggregation Operator (CWA) that captures the nuanced relationships between contexts and parameters in QNSS, providing a flexible aggregation mechanism that not only accounts for the varying importance of different contexts but also emphasizes the multiplicative relationships between membership values. Our framework presents neutrosophic best-worst method to compute criteria weights by ensuring more diverse and well-distributed criteria values and introduces a regularization-based spread maximization function to prevent weight convergence and ensure proper consistency handling through a nonlinear optimization model. Then, a customized fuzzy ARAS is computed to assess and rank the different playing strategies. Further, we introduce a real case study on European volleyball championship for senior men's national teams in Europe, in which decision-makers. Proof of concept analysis is conducted on real case studies validated to the advantages of the proposed approach, and compared the methods against state-of-the-art studies, implying insightful boosting to the opponent analysis and game planning.

Keywords: Neutrosophic Logic (NL), Neutrosophic Sets (NS), Uncertainty Modeling, Multi-valued Logic, Tactical Decision-Making, Volleyball Match Analysis.

1. Introduction

In the competitive landscape of college volleyball, the ability to analyzes opponents and formulate effective gaming strategies is crucial for team success [1]. Coaches and analysts traditionally rely on statistical models, game footage analyses, and expert intuition to devise strategies. However, these conventional methods often struggle to account for the inherent uncertainties and dynamics nature of the game [2]. Factors such as player fatigue, unpredictable injuries, real-time tactical adjustments, and psychological factors introduce a degree of indeterminacy that traditional analysis technique fail to capture effectively [3].

Traditional opponent analysis methods depend on crisp values, predefined probabilistic models, and deterministic approachs that assume complete knowledge about game situations [4].

However, real-world volleyball matches are dynamic, where performances of players varied, tactical formations change, and unexpected circumstances arise [5]. For example, the player's past performance did not guarantee the same efficiency in the subsequent matches because off outside variables e.g., stress, fatigue, or variety within game environments. Coaches often face ambiguous situations where multiple strategies appear viable, but the best decision remained unclear. Existing systems depend on pre-analyzed data, making it difficult to regulate to unforeseen in-game developments [6].

Neutrosophic theory introduces a three-dimensional representation of knowledge—Truth (T), Indeterminacy (I), and Falsity (F)—which can better model the complexities and uncertainties in volleyball strategy formulation [7], [8]. Apart from out-of-date binary or probabilistic models, neutrosophic logic enabled partial truths and indeterminate knowledge, which make it it well-suited for decision-making (DM) in sports [9].

In this article, we aimed to develop a neutrosophic patterns of player performance variability and game uncertainties. Then, we aim to integrate a decision-support system to dynamically adjusted strategies with respects to historical data. This collectively aims to build a unified framework that can be applied to coaching strategies thereby improving the DM in competitive volleyball. To achieve this objective, this study contributes to the body of knowledge through introducing a novel application of neutrosophic logic in opponent analysis as well as strategy formulation for volleyball colleges. The key contributions are summarized as follows. First, a mathematical model for aggregating uncertainty in multi factor assessment of volleyball strategies. Second, a customized weighting mechanism to highlight the importance of different components in analyzing opponent teams. To validate decision-making ability of our approach, we introduce a practical case study where a college volleyball coach analyzes different game strategies under uncertain conditions. A reasonable set of conclusive analysis established the compensations of our methods over previously developed approaches.

The left part of this articles contains five main sections. Background and related literature are described in Section 2. Section 3 explain the methodology of proposed framework in details. The experimental design is debated in Section 4. The results and analysis are discussed in Section 5. The conclusion of article is derived in Section 6.

2. Background and Literature

This section presents a background on the main concepts neutrosophic methods along with the related studies, including essential definitions.

Definition 1 ([7], [8]**)**. With an assumption of $\mathcal{U}$ as a universe of discourse, neutrosophic set $\aleph$ can be defined as:

$$\aleph = \{\langle u,(T_{\aleph}(u),I_{\aleph}(u),F_{\aleph}(u))\rangle : u \in \mathcal{U}\},$$
$$\text{where} \tag{1}$$
$$T_{\aleph}(u), I_{\aleph}(u), F_{\aleph}(u): \mathcal{U} \to]^{-}0, 1^{+}[\text{ and } {}^{-}0 \le T_{\aleph}(u) + I_{\aleph}(u) + F_{\aleph}(u) \le 3^{+}$$

Definition 2 ([10]**)**. With assumption of $\mathcal{U}$ as a universe of discourse and Q as a nonempty set, then the Q-neutrosophic set, $\aleph_Q$, is articulated follows:

$$\aleph_Q = \{\langle(u, q), T_{\aleph_Q}(u, q), I_{\aleph_Q}(u, q), F_{\aleph_Q}(u, q)\rangle : u \in \mathcal{U}, q \in Q\},$$
$$\text{where}$$
$$T_{\aleph_Q}, I_{\aleph_Q}, F_{\aleph_Q} : \mathcal{U} \times Q \to]^-0, 1^+[\text{ and } ^-0 \le T_{\aleph_Q} + I_{\aleph_Q} + F_{\aleph_Q} \le 3^+ \quad (2)$$

Definition 3 ([10]**)**. With assumption of $\mathcal{U}$ as a universe of discourse and Q as a nonempty set, l be any positive integer and I be a unit interval [0,1], then multi Q-neutrosophic set $\widetilde{\aleph}_Q$ in $\mathcal{U}$ and Q is a set of ordered sequences

$$\widetilde{\aleph}_Q = \{\langle(u, q), T_{\widetilde{\aleph}_{Q_i}}(u, q), I_{\widetilde{\aleph}_{Q_i}}(u, q), F_{\widetilde{\aleph}_{Q_i}}(u, q)\rangle : u \in \mathcal{U}, q \in Q$$
$$\text{where}$$
$$T_{\widetilde{\aleph}_{Q_i}}, I_{\widetilde{\aleph}_{Q_i}}, F_{\widetilde{\aleph}_{Q_i}} : \mathcal{U} \times Q \to I^l \; for\ all\ i = 1,2, \dots, l$$
$$0 \le T_{\widetilde{\aleph}_{Q_i}} + I_{\widetilde{\aleph}_{Q_i}} + F_{\widetilde{\aleph}_{Q_i}} \le 3 \; for\ all\ i = 1,2, \dots, l \quad (3)$$

Definition 4 ([11]**)**. Given $\mathcal{U}$ as a universe of discourse, Q as a nonempty set, and E as set of parameters, and Q-neutrosophic sets, $\mu^l QNS(\mathcal{U})$, with dimension $l = 1$, then, a Q-neutrosophic soft set (QNSS) can be define as follows:

$$\aleph_Q : X \to \mu^l QNS(\mathcal{U}) \text{ such that } X \subseteq E \text{ and } \aleph_Q(e) = \phi \text{ if } e \notin X \quad (4)$$

QNSS can be represented by the set of ordered pairs

$$(\aleph_Q, X) = \{(e, \aleph_Q(e)) : e \in X, \aleph_Q \in \mu^l QNS(\mathcal{U})\}. \quad (5)$$

Example 1: In college volleyball, coaches analyze opponent teams, $\mathcal{U} = \{T1, T2, T3\}$, to formulate the best game strategy. The location at which match is played can affect team performance, leading two conditions $Q = \{played - home\ (q_1),\ or\ away\ (q_2)\}$.The analysis is based on key performance indicators, $E = \{\mathrm{e_1} = \text{Offensive Strength}, \mathrm{e_2} = \text{Defensive Weakness}\}$ as a set of decision parameters. Then the QNSS $(\aleph_\mathrm{Q}, \mathrm{A})$ can be derived as follows:

$$(\aleph_Q, X) = \left\{ \begin{array}{c} \left\langle \begin{array}{c} e_1, [(u_1, q_1), 0.8,0.2,0.3], [(u_1, q_2), 0.6,0.3,0.4], [(u_2, q_1), 0.9,0.1,0.2], [(u_2, q_2), 0.7,0.2,0.3], \\ [(u_3, q_1), 0.4,0.5,0.6], [(u_3, q_2), 0.5,0.3,0.4] \end{array} \right\rangle \\ \left\langle \begin{array}{c} e_2, [(u_1, p), 0.3,0.4,0.8], [(u_1, q_2), 0.8,0.4,0.1], [(u_2, q_1), 0.5,0.5,0.8], [(u_2, q_2), 0.2,0.4,0.5], \\ [(u_3, q_1), 0.7,0.3,0.2], [(u_3, q_2), 0.6,0.4,0.3] \end{array} \right\rangle \end{array} \right\}$$

Definition 5 ([10],[11]**)**. Given two subsets $(\aleph_Q, X) = \left\{\left(T_{\aleph_{Q(e_j)}}(u, q)_i, I_{\aleph_{Q(e_j)}}(u, q)_i, F_{\aleph_{Q(e_j)}}(u, q)_i\right) : \forall e_j \in X, (u, q)_i \in \mathcal{U} \times Q\right\} \in QNSS(\mathcal{U})$ and $(\Psi_Q, Y) = \left\{\left(T_{\Psi_{Q(e_j)}}(u, q)_i, I_{\Psi_{Q(e_j)}}(u, q)_i, F_{\Psi_{Q(e_j)}}(u, q)_i\right) : \forall e_j \in Y, (u, q)_i \in \mathcal{U} \times Q\right\} \in Q -$

$NSS(\mathcal{U})$, then the (Ψ_Q, Y) can be declared as subset of $(\aleph_Q, X)$ if $Y \subseteq X$ and $\Psi_Q(u) \subseteq \aleph_Q(u)$ for all $u \in \mathcal{U}$.

$$X \subseteq Y \ \& \ \aleph_Q(e) \subseteq \Psi_Q(e) \forall e \in X$$
where
$$T_{\aleph_{Q(e)}}(u, q) \le T_{\Psi_{Q(e)}}(u, q),$$
$$I_{\aleph_{Q(e)}}(u, q) \ge I_{\Psi_{Q(e)}}(u, q), F_{\aleph_{Q(e)}}(u, q) \ge F_{\Psi_{Q(e)}}(u, q), \forall (u, q) \in \mathcal{U} \times Q \tag{6}$$

Definition 6 ([10],[11]). Given two QNSSs $(\aleph_Q, X) = \left\{\left(T_{\aleph_{Q(e)}}(u, q), I_{\aleph_{Q(e)}}(u, q), F_{\aleph_{Q(e)}}(u, q)\right) : \forall e \in X, (u, q) \in \mathcal{U} \times Q\right\}$ and $(\Psi_Q, Y) = \left\{\left(T_{\Psi_{Q(e)}}(u, q), I_{\Psi_{Q(e)}}(u, q), F_{\Psi_{Q(e)}}(u, q)\right) : \forall e \in Y, (u, q) \in \mathcal{U} \times Q\right\}$, the union of these two sets can be symbolized as $(\cup_Q, C) = (\aleph_Q, A) \cup (\Psi_Q, B)$, in which the membership functions are computed as follows:

$$T_{\cup_{Q(c)}}(u, q) = \begin{cases} T_{\aleph_{Q(c)}}(u, q) & if c \in X - Y, \\ T_{\Psi_{Q(c)}}(u, q) & if c \in Y - X, \\ max\{T_{\Lambda_{Q(c)}}(u, q), T_{\Psi_{Q(c)}}(u, q)\} & if c \in X \cap Y, \end{cases}$$
$$I_{\cup_{Q(c)}}(u, q) = \begin{cases} I_{\aleph_{Q(c)}}(u, q) & if c \in X - Y, \\ I_{\Psi_{Q(c)}}(u, q) & if c \in Y - X, \\ \min\left\{I_{\aleph_{Q(c)}}(u, q), I_{\Psi_{Q(c)}}(u, q)\right\} & if c \in X \cap Y, \end{cases} \tag{7}$$
$$F_{\cup_{Q(c)}}(u, q) = \begin{cases} F_{\aleph_{Q(c)}}(u, q) & if c \in X - Y, \\ F_{\Psi_{Q(c)}}(u, q) & if c \in Y - X, \\ min\{F_{\aleph_{Q(c)}}(u, q), F_{\Psi_{Q(c)}}(u, q)\} & if c \in X \cap Y. \end{cases}$$

where $C = A \cup B$ and $c \in C, (u, q) \in U \times Q$.

Definition 7 ([10],[11]). Given two QNSSs $(\aleph_Q, X) = \left\{\left(T_{\aleph_{Q(e)}}(u, q), I_{\aleph_{Q(e)}}(u, q), F_{\aleph_{Q(e)}}(u, q)\right) : \forall e \in X, (u, q) \in \mathcal{U} \times Q\right\}$ and $(\Psi_Q, Y) = \left\{\left(T_{\Psi_{Q(e)}}(u, q), I_{\Psi_{Q(e)}}(u, q), F_{\Psi_{Q(e)}}(u, q)\right) : \forall e \in Y, (u, q) \in \mathcal{U} \times Q\right\}$, the intersection of these two sets can be symbolized as $(\cap_Q, C) = (\aleph_Q, X) \cap (\Psi_Q, Y)$, in which the membership functions are computed as follows:

$$T_{\cap_{Q(c)}}(u, q) = min\left\{T_{\aleph_{Q(c)}}(u, q), T_{\Psi_{Q(c)}}(u, q)\right\},$$
$$I_{\cap_{Q(c)}}(u, q) = max\left\{I_{\aleph_{Q(c)}}(u, q), I_{\Psi_{Q(c)}}(u, q)\right\}, \tag{8}$$
$$F_{\cap_{Q(c)}}(u, q) = max\left\{F_{\aleph_{Q(c)}}(u, q), F_{\Psi_{Q(c)}}(u, q)\right\}.$$

Definition 8 ([10],[11]**)**. Given an $QNSSs$ $\left(\aleph_Q, X\right) = \left\{\left(T_{\aleph_{Q(\mathrm{e})}}(u, q), I_{\aleph_{Q(e)}}(u, q), F_{\aleph_{Q(\mathrm{e})}}(u, q)\right) : \forall e \in X, (u, q) \in \mathcal{U} \times Q\right\}$, then, its complement is defined as $(\aleph_Q, X)^c = (\aleph_Q^c, X)$,

$$(\aleph_Q, X)^c = \left\{\langle e, T^c_{\aleph_{Q(e)}}(u, q), I^c_{\aleph_{Q(e)}}(u, q), F^c_{\aleph_{Q(e)}}(u, q)\rangle : e \in X, (u, q) \in U \times Q\right\}, \tag{9}$$

such that $\forall e \in X, (u, q) \in \mathcal{U} \times Q$

$$\begin{aligned} T^c_{\aleph_{Q(e)}}(u, q) &= 1 - T_{\aleph_{Q(e)}}(u, q), \\ I^c_{\aleph_{Q(e)}}(u, q) &= 1 - I_{\aleph_{Q(e)}}(u, q), \\ F^c_{\aleph_{Q(e)}}(u, q) &= 1 - F_{\aleph_{Q(e)}}(u, q). \end{aligned}$$

Example 2. Based on example 1, the complement of $(\aleph_Q, X)$ is expressed as follows:

$$\left(\aleph_Q, X\right) = \left\{\begin{array}{c} \left\langle \begin{array}{c} e_1, [(u_1, q_1), 0.2,0.8,0.7], [(u_1, q_2), 0.4,0.7,0.6], [(u_2, q_1), 0.1,0.9,0.8], [(u_2, q_2), 0.3,0.8,0.7], \\ [(u_3, q_1), 0.6,0.5,0.4], [(u_3, q_2), 0.5,0.7,0.6] \end{array} \right\rangle \\ \left\langle \begin{array}{c} e_2, [(u_1, p), 0.7,0.6,0.2], [(u_1, q_2), 0.8,0.4,0.1], [(u_2, q_1), 0.5,0.5,0.8], [(u_2, q_2), 0.8,0.6,0.5], \\ [(u_3, q_1), 0.3,0.7,0.8], [(u_3, q_2), 0.4,0.6,0.7] \end{array} \right\rangle \end{array}\right\}$$

Definition 9 ([10],[11]**)**. Given $\left(\aleph_Q, X\right) \in QNSS(\mathcal{U})$, $\aleph_Q(e) = \phi$ for all $e \in X$, then $\left(\aleph_Q, X\right)$ can be declared as a null $QNSS(\mathcal{U})$, and is referred to as (ϕ, X).

Definition 10 ([10],[11]). Given an QNSSs $\left(\aleph_Q, X\right) = \left\{\left(T_{\aleph_{Q(\mathrm{e})}}(u, q), I_{\aleph_{Q(e)}}(u, q), F_{\aleph_{Q(\mathrm{e})}}(u, q)\right) : \forall e \in X, (u, q) \in \mathcal{U} \times Q\right\}$, then, the necessity operation can be defined as:

$$\oplus\, (\aleph_Q, X) = \left\{\langle e, [(u, q), T_{\aleph_Q}(u, q), I_{\aleph_Q}(u, q), 1 - T_{\aleph_Q}(u, q)]\rangle : (u, q) \in U \times Q\right\}. \tag{10}$$

Example 3. Based on example 1, the necessity operation of $(\aleph_Q, X)$ is computed as follows:

$$\oplus\left(\aleph_Q, X\right) = \left\{\begin{array}{c} \left\langle \begin{array}{c} e_1, [(u_1, q_1), 0.8,0.2,0.2], [(u_1, q_2), 0.6,0.3,0.4], [(u_2, q_1), 0.9,0.1,0.1], [(u_2, q_2), 0.7,0.2,0.3], \\ [(u_3, q_1), 0.4,0.5,0.6], [(u_3, q_2), 0.5,0.3,0.5] \end{array} \right\rangle \\ \left\langle \begin{array}{c} e_2, [(u_1, p), 0.3,0.4,0.7], [(u_1, q_2), 0.8,0.4,0.2], [(u_2, q_1), 0.5,0.5,0.5], [(u_2, q_2), 0.2,0.4,0.8], \\ [(u_3, q_1), 0.7,0.3,0.3], [(u_3, q_2), 0.6,0.4,0.4] \end{array} \right\rangle \end{array}\right\}$$

Definition 11 ([10],[11]**)**.Given an QNSSs $\left(\aleph_Q, X\right) = \left\{\left(T_{\aleph_{Q(\mathrm{e})}}(u, q), I_{\aleph_{Q(e)}}(u, q), F_{\aleph_{Q(\mathrm{e})}}(u, q)\right) : \forall e \in X, (u, q) \in \mathcal{U} \times Q\right\}$, then, the possibility operation can be defined as:

$$\otimes\, (\aleph_Q, X) = \left\{\langle e, [(u, q), 1 - F_{\aleph_Q}(u, q), I_{\aleph_Q}(u, q), F_{\aleph_Q}(u, q)]\rangle : (u, q) \in U \times Q\right\}. \tag{11}$$

Definition 12 ([12]**).** Given $X = \{u_1, u_2, \dots, u_m\}$, $Q = \{q_1, q_2, \dots, q_l\}$, and $X = \{e_1, e_2, \dots, e_n\}$, then, the hamming distance between two QNSSs $(\aleph_Q, X)$, and $(\aleph_Q, Y)$ is defined as follows:

$$d_{QNSS}^{Hamm}\left((\aleph_Q, X), (\Psi_Q, Y)\right) = \sum_{j=1}^{n}\sum_{i=1}^{lm}\frac{\left|T_{\aleph_Q(e_j^X)}(u,q)_i - T_{\Psi_Q(e_j^Y)}(u,q)_i\right| + \left|I_{\aleph_Q(e_j^X)}(u,q)_i - I_{\Psi_Q(e_j^Y)}(u,q)_i\right| + \left|F_{\aleph_Q(e_j^X)}(u,q)_i - F_{\Psi_Q(e_j^Y)}(u,q)_i\right|}{3}, \tag{12}$$

Definition 13 ([12]**).** Given $X = \{u_1, u_2, \dots, u_m\}$, $Q = \{q_1, q_2, \dots, q_l\}$, and $X = \{e_1, e_2, \dots, e_n\}$, then, the excluding distance between two QNSSs $(\aleph_Q, X)$, and $(\aleph_Q, Y)$ is defined as follows:

$$d_{QNSS}^{Eclud}\left((\aleph_Q, X), (\Psi_Q, Y)\right) = \sum_{j=1}^{n}\sum_{i=1}^{lm}\sqrt{\frac{\left(T_{\aleph_Q(e_j^X)}(u,q)_i - T_{\Psi_Q(e_j^Y)}(u,q)_i\right)^2 + \left(I_{\aleph_Q(e_j^X)}(u,q)_i - I_{\Psi_Q(e_j^Y)}(u,q)_i\right)^2 + \left(F_{\aleph_Q(e_j^X)}(u,q)_i - F_{\Psi_Q(e_j^Y)}(u,q)_i\right)^2}{3}}, \tag{13}$$

3. Theoretical Framework & Methodology

In this section, we present a neutrosophic-based methodology for opponent analysis in college volleyball. Our proposed approach integrates a sequence of systematic steps for modeling opponent performance and evaluating strategic choices.

3.1. Context-aware Aggregator

Definition 14: Given a QNSS $(\aleph_Q, A)$ over U, a QNS aggregator for $(\aleph_Q, A)$, symbolized by $\aleph_Q^{agg}$ and is $\aleph_Q^{agg} = \{\langle (u,t), T_Q^{agg}(u,t), I_Q^{agg}(u,t), F_Q^{agg}(u,t)\rangle : (u,t) \in U \times Q\}$, such that

$$T_Q^{agg} = \frac{1}{|A|}\sum_{(u,t)\in U\times Q} T_{\aleph_Q}(u,t), I_Q^{agg} = \frac{1}{|A|}\sum_{(u,t)\in U\times Q} I_{\aleph_Q}(u,t), \quad F_Q^{agg} = \frac{1}{|A|}\sum_{(u,t)\in U\times Q} F_{\aleph_Q}(u,t). \tag{14}$$

where $T_Q^{agg}, I_Q^{agg}, F_Q^{agg}: U \times Q \to [0,1]$.

Example 4: Consider a college volleyball team is preparing for an important playoff match and must decide on the best defensive strategy against a strong attacking opponent. The coaching staff evaluates three opponent teams, $U = \{u_1, u_2, u_3\}$, based on their attacking styles under different match scenarios, $Q = \{q_1: Serve\ Reception\ Phase\ , q_2: Transition\ Phase\}$, using key defensive evaluation criteria, $E = \{e_1: Blocking\ Efficiency\ , e_2: Digging\ Success\ , e_3: Opponent\ Disruption\}$. Then, expert drive the following QNSS:

$$(\aleph_Q, A) = \left\{\begin{matrix} \langle e_1, [(u_1, q_1), 0.3,0.4,0.3], [(u_1, q_2), 0.7,0.3,0.1], [(u_2, q_1), 0.2,0.5,0.3], [(u_3, q_2), 0.4,0.2,0.4]\rangle \\ \langle e_2, [(u_1, q_1), 0.5,0.2,0.3], [(u_2, q_1), 0.6,0.3,0.1], [(u_3, q_1), 0.4,0.4,0.2], [(u_3, q_2), 0.3,0.3,0.4]\rangle \\ \langle e_3, [(u_1, q_2), 0.4,0.3,0.3], [(u_2, q_2), 0.8,0.2,0.1]\rangle \end{matrix}\right\}$$

By applying Q-NS Aggregation Operator, the following QNSS is obtained:

$$\aleph_Q^{agg} = \left\{\begin{matrix} [(u_1, q_1), 0.267,0.20,0.20], \\ [(u_1, q_2), 0.366,0.20,0.133], \\ [(u_2, q_1), 0.267,0.267,0.133], \\ [(u_2, q_2), 0.267,0.067,0.033], \\ [(u_3, q_1), 0.133,0.133,0.066], \\ [(u_3, q_2), 0.233,0.166,0.267] \end{matrix}\right\}$$

While the Q-NS aggregation operator was developed as a robust tool for DM within uncertainty problems, it has some notable confines that can be prudently considered in real-world application. One major limitation is that the aggregation operator chiefly emphases on pairing elements from the universe of alternatives (i.e., volleyball teams) with the set of contexts (i.e., match scenarios), while neglecting direct relationships between the criteria themselves and the alternatives. This results in a loss of inter-criteria dependencies. In many DM scenarios, criteria are not independent but rather interrelated. For example, in the hiring scenario, experience might have a strong correlation with language fluency, meaning that candidates with more experience are also likely to have better fluency. However, the aggregation method collapses these relationships by averaging them, rather than maintaining their interactions. Moreover, the method does not preserve the original decision space structure, making it difficult to justify why a particular alternative was ranked higher, as the detailed assessment per criterion is lost in the overall summary values.

To address these limitations, we propose a context-wise aggregation operator (CWAO) multi-context behavior in QNSS effectually by carrying out aggregation distinctly from all contexts $q \in Q$ and then combine the resulting component in a meaningful way for each parameter. This way, our CWAO provide a more nuanced and flexible approach to capture the diverse features of each context while addressing issues such as unequal importance, and uncertainty in membership values.

Definition 15. Given a QNSS $(\aleph_Q, A)$ over U, a QNS aggregator for $(\aleph_Q, A)$, symbolized by $\aleph_{\mathrm{Q}}^{\mathrm{agg}}$ and is $\aleph_Q^{agg} = \{\langle (u,t), T_Q^{agg}(u,t), I_Q^{agg}(u,t), F_Q^{agg}(u,t)\rangle : (u,t) \in U \times Q\}$, such that

(15)

$$T^{agg}(u,e) = \frac{1}{|Q|}\sum_{(u,e)\in U\times E}\left(T_{\aleph_Q}(u,e)\right) - \left(\prod_{(u,e)\in U\times E}\left(T_{\aleph_Q}(u,e)\right)^{w_q}\right),$$
$$I^{agg}(u,e) = \frac{1}{|Q|}\sum_{(u,e)\in U\times E}\left(I_{\aleph_Q}(u,e)\right) - \left(\prod_{(u,e)\in U\times E}\left(I_{\aleph_Q}(u,e)\right)^{w_q}\right),$$
$$F^{agg}(u,e) = \frac{1}{|Q|}\sum_{(u,e)\in U\times E}\left(F_{\aleph_Q}(u,e)\right) - \left(\prod_{(u,e)\in U\times E}\left(F_{\aleph_Q}(u,e)\right)^{w_q}\right).$$

where w_q is the weight for context q, such that $\sum_{q\in Q} w_q = 1$.

Example 5: Given the weights $w_{q_1} = 0.6$, and $w_{q_2} = 0.4$, the result of applying CWAO to Example result in the following QNSS:

$$\aleph_Q^{agg} = \begin{Bmatrix} [(e_1,u_1), 0.554, 0.346, 0.195], [(e_1,u_1), 0.2, 0.5, 0.3], [(e_1,u_3), 0.4, 0.2, 0.4] \\ [(e_2,u_1), 0.5, 0.2, 0.3], [(e_2,u_2), 0.6, 0.3, 0.1], [(e_2,u_3), 0.346, 0.346, 0.202] \\ [(e_3,u_1), 0.4, 0.3, 0.3], [(e_3,u_2), 0.8, 0.2, 0.1] \end{Bmatrix}$$

To voids excessive reduction of values caused by the multiplications of fractional membership values in, we decide to modify the CWAO formula by raising the membership values to inverse of weight value.

Definition 16. Given a QNSS $(\aleph_Q, A)$ over U, a QNS aggregator for $(\aleph_Q, A)$, symbolized by $\aleph_{\mathrm{Q}}^{\mathrm{agg}}$ and is $\aleph_Q^{agg} = \{\langle (u,t), T_Q^{agg}(u,t), I_Q^{agg}(u,t), F_Q^{agg}(u,t)\rangle : (u,t) \in U \times Q\}$, such that

$$T^{agg}(u,e) = \frac{1}{|Q|}\sum_{(u,e)\in U\times E}\left(T_{\aleph_Q}(u,e)\right) - \left(\prod_{(u,e)\in U\times E}\left(T_{\aleph_Q}(u,e)\right)^{\frac{1}{w_q}}\right),$$
$$I^{agg}(u,e) = \frac{1}{|Q|}\sum_{(u,e)\in U\times E}\left(I_{\aleph_Q}(u,e)\right) - \left(\prod_{(u,e)\in U\times E}\left(I_{\aleph_Q}(u,e)\right)^{\frac{1}{w_q}}\right), \quad (16)$$
$$F^{agg}(u,e) = \frac{1}{|Q|}\sum_{(u,e)\in U\times E}\left(F_{\aleph_Q}(u,e)\right) - \left(\prod_{(u,e)\in U\times E}\left(F_{\aleph_Q}(u,e)\right)^{\frac{1}{w_q}}\right).$$

where w_q is the weight for context q, such that $\sum_{q\in Q} w_q = 1$.

3.1. Decision-making application

The Fuzzy Best-Worst Method (Fuzzy BWM) [13] was developed as DM tool that integrate expert preferences using fuzzy logic to handle uncertainty. However, in our case, uncertainty arises in multiple contexts, which motivate proposing new extension called QNSS-BWM. QNSS-BWM is developed to compute criteria weights in a the aggregated QNSS decision matrix. given a set of decision criteria, the QNSS-BWM follows these steps to compute the weights.

In step 1, we define the decision criteria $C = \{C_1, C_2, \dots, C_n\}$ with best criterion denoted as C_B, and worst criterion noted as C_W. Both of them are determined by expert knowledge.

In step 2, we drive preference vector for the best criterion as:

$$QBO_B = \{QNN_{B1}, QNN_{B2}, \dots, QNN_{Bn}\} \tag{17}$$

where $QNN_{Bi} = (T_{Bi}, I_{Bi}, F_{Bi})$

Each entry represents how much better the best criterion C_B is compared to C_i. For the best criterion itself:$QNN_{BB} = (1,0,0)$.

In step 3, we calculate Q-Neutrosophic Best-to-Others (QBO) Matrix

$$QB_M = \begin{bmatrix} (1,0,0) & QNN_{B1} & QNN_{B2} & \cdots & QNN_{Bn} \\ \frac{1}{QNN_{B1}} & (1,0,0) & \frac{QNN_{B2}}{QNN_{B1}} & \cdots & \frac{QNN_{Bn}}{QNN_{B1}} \\ \frac{1}{QNN_{B2}} & \frac{QNN_{B1}}{QNN_{B2}} & (1,0,0) & \cdots & \frac{QNN_{Bn}}{QNN_{B2}} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \frac{1}{QNN_{Bn}} & \frac{QNN_{B1}}{QNN_{Bn}} & \frac{QNN_{B2}}{QNN_{Bn}} & \cdots & (1,0,0) \end{bmatrix} \tag{18}$$

and similarly calculate Neutrosophic Others-to-Worst (QOW) Matrix

$$QW_M = \begin{bmatrix} (0,1,1) & \frac{1}{QNN_{1W}} & \frac{1}{QNN_{2W}} & \cdots & \frac{1}{QNN_{nW}} \\ QNN_{1W} & (0,1,1) & \frac{QNN_{2W}}{QNN_{1W}} & \cdots & \frac{QNN_{nW}}{QNN_{1W}} \\ QNN_{2W} & \frac{QNN_{1W}}{QNN_{2W}} & (0,1,1) & \cdots & \frac{QNN_{nW}}{QNN_{2W}} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ QNN_{nW} & \frac{QNN_{1W}}{QNN_{nW}} & \frac{QNN_{2W}}{QNN_{nW}} & \cdots & (0,1,1) \end{bmatrix} \tag{19}$$

In step 4, we calculate QNSS-BWM weights $W = (w_1, w_2, \dots, w_n)$ by solving the following:

$$\min \xi \text{ subject to:} \tag{20}$$

$$\left|\frac{w_B}{w_i} - T_{Bi}\right| \leq \xi,\ \forall i$$
$$\left|\frac{w_i}{w_W} - T_{iW}\right| \leq \xi,\ \forall i$$
$$\sum_{i=1}^{n} w_i = 1,\ w_i \geq 0,\ \forall i$$

By computing the weights, we can get back to the aggregated decision matrix is formulated as:

$$D = \begin{bmatrix} (T_{11}, I_{11}, F_{11}) & (T_{12}, I_{12}, F_{12}) & \dots & (T_{1n}, I_{1n}, F_{1n}) \\ (T_{21}, I_{21}, F_{21}) & (T_{22}, I_{22}, F_{22}) & \dots & (T_{2n}, I_{2n}, F_{2n}) \\ \vdots & \vdots & \ddots & \vdots \\ (T_{m1}, I_{m1}, F_{m1}) & (T_{m2}, I_{m2}, F_{m2}) & \dots & (T_{mn}, I_{mn}, F_{mn}) \end{bmatrix} \tag{21}$$

In step 5, we normalize the matrix to ensure all criteria are comparable. For benefit criteria and cost criteria, the normalization formulas are:

$$\begin{gathered} T_{ij}^* = \frac{T_{ij}}{\max(T_j)},\ I_{ij}^* = \frac{I_{ij}}{\max(I_j)},\ F_{ij}^* = \frac{F_{ij}}{\max(F_j)}, \\ T_{ij}^* = \frac{\min(T_j)}{T_{ij}},\ I_{ij}^* = \frac{\min(I_j)}{I_{ij}},\ F_{ij}^* = \frac{\min(F_j)}{F_{ij}} \end{gathered} \tag{22}$$

The normalized matrix is formulated as:

$$D^* = \begin{bmatrix} (T_{11}^*, I_{11}^*, F_{11}^*) & (T_{12}^*, I_{12}^*, F_{12}^*) & \dots & (T_{1n}^*, I_{1n}^*, F_{1n}^*) \\ (T_{21}^*, I_{21}^*, F_{21}^*) & (T_{22}^*, I_{22}^*, F_{22}^*) & \dots & (T_{2n}^*, I_{2n}^*, F_{2n}^*) \\ \vdots & \vdots & \ddots & \vdots \\ (T_{m1}^*, I_{m1}^*, F_{m1}^*) & (T_{m2}^*, I_{m2}^*, F_{m2}^*) & \dots & (T_{mn}^*, I_{mn}^*, F_{mn}^*) \end{bmatrix}. \tag{23}$$

In step 6, we assign weights w_j to each criterion e_j, such that $\sum_{j=1}^{n} w_j = 1$. The weighted normalized matrix is:

$$D^w = \begin{bmatrix} (w_1 T_{11}^*, w_1 I_{11}^*, w_1 F_{11}^*) & (w_2 T_{12}^*, w_2 I_{12}^*, w_2 F_{12}^*) & \dots & (w_n T_{1n}^*, w_n I_{1n}^*, w_n F_{1n}^*) \\ (w_1 T_{21}^*, w_1 I_{21}^*, w_1 F_{21}^*) & (w_2 T_{22}^*, w_2 I_{22}^*, w_2 F_{22}^*) & \dots & (w_n T_{2n}^*, w_n I_{2n}^*, w_n F_{2n}^*) \\ \vdots & \vdots & \ddots & \vdots \\ (w_1 T_{m1}^*, w_1 I_{m1}^*, w_1 F_{m1}^*) & (w_2 T_{m2}^*, w_2 I_{m2}^*, w_2 F_{m2}^*) & \dots & (w_n T_{mn}^*, w_n I_{mn}^*, w_n F_{mn}^*) \end{bmatrix} \tag{24}$$

In step 7, we compute the neutrosophic score

$$S_i = \left(\sum_{j=1}^{n} w_j T_{ij}^*, \sum_{j=1}^{n} w_j I_{ij}^*, \sum_{j=1}^{n} w_j F_{ij}^* \right) \tag{25}$$

Finally, we convert the optimality function into a crisp value using a defuzzification method. Then, rank alternatives based on utility degree:

$$S_i = \frac{\left(S_i^T + S_i^I + S_i^F\right)}{3}$$
$$D_i = \frac{S_i}{S} \tag{26}$$

We rank the alternatives according to D_i. The alternative with the highest D_i is the best choice.

4. Data Collection & Opponent Profiling

To validate the effectiveness of the proposed neutrosophic-based framework in opponent analysis and game strategy formulation, we apply it to a real-world college volleyball scenario. This case study aims to demonstrate how a multi-criteria decision model can improve strategy selection under indeterminate conditions. In this case study, we analyze potential starting lineups for an upcoming championship match, evaluating them based on key performance criteria. A college volleyball team is preparing for a crucial championship match and must decide on the best starting lineup. The selection process is complex due to contradicting factors such as player performance and fatigue/injury risks. The coach must evaluate potential starting lineups while considering different critical criteria. These criteria include Offensive Efficiency (Benefit), Defensive Stability (Benefit), Opponent Disruption (Benefit), Energy Consumption (Cost), Tactical Complexity (Cost), and Injury Risk (Cost). Using these set of criteria, the coach carefully evaluates multiple strategic alternatives to optimize the team's performance against a strong opponent. As tabulated in Table 1, the coach considers eight alternative strategies, each with distinct advantages and trade-offs. These strategies are assessed with respect to different criteria, which include both benefit-oriented factors and cost-related factors.

Table 1: Overview of Alternative Game Strategies and Their Tactical Characteristics in College Volleyball.

Alternative Tactics	Description	**ID**
Aggressive Attack Focus	Prioritizing the power of spiking, fast tempo offense, as well as fast attacks.	A1
Defensive Block-Oriented Play	Emphasizing hard obstructive creations and robust back-row defense.	A2
Serve-Pressure Strategy	Usage of high-risk, high-reward serves for disruption of opponent's transitory.	A3
Balanced Offense-Defense Play	Mechanism for moderating intensity of attack and organized defense.	A4
Quick Rotation & Substitution Strategy	Recurrent rotations of player to uphold energy and deed matchups.	A5
Targeted Weakness Exploitation	Emphasis attacking the weakest opponent defenders.	A6
Adaptive Tactical Shifts	Instantons adjustments in response to opponent's strategy shifts.	A7
Set-Variation Strategy	Vicissitudes offensive play style unpredictably to confuse the opponent.	A8

To ensure a robust and objective assessment of each game strategy, we obtained team evaluations from three coaching experts. These experts, with extensive experience in college volleyball coaching, assessed the strategies based on key performance criteria. Each expert provided an independent evaluation of eight strategic alternatives under three different match conditions namely Home Matches (H), Away Matches (A), and Neutral Venue Matches (N). Tables 2-4 resents the neutrosophic evaluations of the eight strategic alternatives according to assessments from three coaching experts.

Table 2. Evaluation of volleyball team based on expert 1 assessments.

Strategy	Q	C1	C2	C3	C4	C5	C6
A1	H	(0.52, 0.48, 0.0)	(0.74, 0.34, 0.16)	(0.39, 0.12, 0.49)	(0.82, 0.34, 0.38)	(0.31, 0.49, 0.2)	(0.8, 0.18, 0.02)
	A	(0.41, 0.17, 0.42)	(0.48, 0.31, 0.21)	(0.56, 0.22, 0.22)	(0.67, 0.16, 0.17)	(0.48, 0.25, 0.27)	(0.57, 0.41, 0.02)
	N	(0.42, 0.31, 0.27)	(0.66, 0.12, 0.22)	(0.66, 0.17, 0.17)	(0.34, 0.48, 0.18)	(0.88, 0.42, 0.22)	(0.36, 0.37, 0.27)
A2	H	(0.56, 0.15, 0.29)	(0.6, 0.11, 0.29)	(0.85, 0.2, 0.37)	(0.49, 0.31, 0.2)	(0.63, 0.17, 0.2)	(0.88, 0.41, 0.48)
	A	(0.84, 0.34, 0.47)	(0.35, 0.18, 0.47)	(0.33, 0.23, 0.44)	(0.53, 0.21, 0.26)	(0.8, 0.24, 0.21)	(0.63, 0.16, 0.21)
	N	(0.78, 0.13, 0.09)	(0.89, 0.41, 0.18)	(0.3, 0.43, 0.27)	(0.72, 0.39, 0.41)	(0.34, 0.24, 0.42)	(0.37, 0.45, 0.18)
A3	H	(0.67, 0.23, 0.1)	(0.34, 0.22, 0.44)	(0.5, 0.39, 0.11)	(0.68, 0.45, 0.29)	(0.37, 0.39, 0.24)	(0.76, 0.32, 0.41)
	A	(0.6, 0.31, 0.09)	(0.56, 0.11, 0.33)	(0.36, 0.11, 0.53)	(0.68, 0.23, 0.09)	(0.61, 0.46, 0.2)	(0.55, 0.4, 0.05)
	N	(0.44, 0.13, 0.43)	(0.47, 0.16, 0.37)	(0.86, 0.42, 0.35)	(0.82, 0.42, 0.17)	(0.84, 0.32, 0.42)	(0.84, 0.23, 0.14)
A4	H	(0.44, 0.27, 0.29)	(0.79, 0.44, 0.1)	(0.61, 0.27, 0.12)	(0.43, 0.15, 0.42)	(0.5, 0.48, 0.02)	(0.49, 0.31, 0.2)
	A	(0.72, 0.25, 0.03)	(0.88, 0.48, 0.2)	(0.6, 0.22, 0.18)	(0.47, 0.11, 0.42)	(0.67, 0.3, 0.03)	(0.33, 0.21, 0.46)
	N	(0.84, 0.2, 0.16)	(0.59, 0.49, 0.2)	(0.7, 0.41, 0.23)	(0.74, 0.25, 0.01)	(0.68, 0.35, 0.31)	(0.35, 0.43, 0.22)
A5	H	(0.49, 0.17, 0.34)	(0.32, 0.34, 0.34)	(0.71, 0.11, 0.18)	(0.61, 0.19, 0.2)	(0.69, 0.17, 0.14)	(0.71, 0.25, 0.04)
	A	(0.86, 0.16, 0.24)	(0.37, 0.47, 0.16)	(0.83, 0.2, 0.36)	(0.79, 0.32, 0.31)	(0.45, 0.14, 0.41)	(0.84, 0.46, 0.35)
	N	(0.5, 0.24, 0.26)	(0.74, 0.46, 0.45)	(0.77, 0.36, 0.13)	(0.4, 0.46, 0.14)	(0.66, 0.1, 0.24)	(0.36, 0.37, 0.27)
A6	H	(0.3, 0.16, 0.54)	(0.63, 0.38, 0.36)	(0.43, 0.38, 0.19)	(0.44, 0.23, 0.33)	(0.75, 0.36, 0.44)	(0.69, 0.33, 0.14)
	A	(0.52, 0.21, 0.27)	(0.45, 0.49, 0.06)	(0.54, 0.46, 0.0)	(0.68, 0.42, 0.3)	(0.65, 0.3, 0.05)	(0.42, 0.39, 0.19)
	N	(0.47, 0.11, 0.42)	(0.69, 0.17, 0.14)	(0.86, 0.48, 0.47)	(0.52, 0.11, 0.37)	(0.86, 0.27, 0.49)	(0.88, 0.44, 0.22)
A7	H	(0.53, 0.44, 0.03)	(0.49, 0.17, 0.34)	(0.63, 0.47, 0.38)	(0.64, 0.14, 0.22)	(0.67, 0.5, 0.16)	(0.61, 0.45, 0.4)
	A	(0.72, 0.38, 0.24)	(0.48, 0.42, 0.1)	(0.79, 0.45, 0.47)	(0.61, 0.3, 0.09)	(0.78, 0.36, 0.38)	(0.78, 0.46, 0.24)
	N	(0.53, 0.14, 0.33)	(0.65, 0.11, 0.24)	(0.58, 0.32, 0.1)	(0.47, 0.34, 0.19)	(0.32, 0.11, 0.57)	(0.79, 0.24, 0.15)
A8	H	(0.61, 0.41, 0.19)	(0.67, 0.13, 0.2)	(0.33, 0.31, 0.36)	(0.62, 0.35, 0.03)	(0.74, 0.49, 0.31)	(0.49, 0.42, 0.09)
	A	(0.46, 0.28, 0.26)	(0.35, 0.11, 0.54)	(0.88, 0.43, 0.38)	(0.55, 0.17, 0.28)	(0.39, 0.2, 0.41)	(0.63, 0.39, 0.36)
	N	(0.47, 0.48, 0.05)	(0.74, 0.32, 0.34)	(0.55, 0.2, 0.25)	(0.51, 0.4, 0.09)	(0.31, 0.15, 0.54)	(0.33, 0.12, 0.55)

Table 3. Evaluation of volleyball team based on expert 2 assessments.

Strategy	Q	C1	C2	C3	C4	C5	C6
A1	H	(0.81, 0.38, 0.29)	(0.36, 0.3, 0.34)	(0.58, 0.17, 0.25)	(0.56, 0.26, 0.18)	(0.67, 0.35, 0.12)	(0.52, 0.35, 0.13)
	A	(0.6, 0.44, 0.36)	(0.4, 0.13, 0.47)	(0.69, 0.11, 0.2)	(0.65, 0.48, 0.33)	(0.53, 0.36, 0.11)	(0.57, 0.32, 0.11)
	N	(0.86, 0.25, 0.48)	(0.84, 0.18, 0.13)	(0.36, 0.11, 0.53)	(0.36, 0.37, 0.27)	(0.34, 0.23, 0.43)	(0.81, 0.11, 0.08)
A2	H	(0.79, 0.21, 0.0)	(0.37, 0.38, 0.25)	(0.68, 0.45, 0.39)	(0.78, 0.21, 0.01)	(0.41, 0.4, 0.19)	(0.78, 0.5, 0.27)
	A	(0.52, 0.41, 0.07)	(0.5, 0.47, 0.03)	(0.82, 0.27, 0.4)	(0.75, 0.14, 0.11)	(0.84, 0.3, 0.43)	(0.49, 0.46, 0.05)
	N	(0.53, 0.1, 0.37)	(0.84, 0.14, 0.02)	(0.49, 0.48, 0.03)	(0.87, 0.33, 0.35)	(0.57, 0.22, 0.21)	(0.5, 0.37, 0.13)
A3	H	(0.75, 0.42, 0.42)	(0.35, 0.3, 0.35)	(0.33, 0.32, 0.35)	(0.56, 0.46, 0.24)	(0.37, 0.16, 0.47)	(0.76, 0.35, 0.14)
	A	(0.35, 0.38, 0.27)	(0.34, 0.43, 0.23)	(0.72, 0.13, 0.15)	(0.35, 0.49, 0.16)	(0.52, 0.25, 0.23)	(0.79, 0.48, 0.49)
	N	(0.75, 0.25, 0.0)	(0.35, 0.41, 0.24)	(0.64, 0.27, 0.09)	(0.84, 0.14, 0.02)	(0.6, 0.1, 0.3)	(0.58, 0.12, 0.3)

A4	H	(0.37, 0.15, 0.48)	(0.69, 0.4, 0.33)	(0.88, 0.25, 0.21)	(0.82, 0.19, 0.49)	(0.31, 0.49, 0.2)	(0.33, 0.46, 0.21)
	A	(0.62, 0.5, 0.13)	(0.63, 0.49, 0.31)	(0.68, 0.38, 0.28)	(0.68, 0.33, 0.46)	(0.33, 0.21, 0.46)	(0.87, 0.46, 0.28)
	N	(0.67, 0.21, 0.12)	(0.41, 0.29, 0.3)	(0.51, 0.33, 0.16)	(0.35, 0.49, 0.16)	(0.89, 0.38, 0.31)	(0.49, 0.43, 0.08)
A5	H	(0.71, 0.17, 0.12)	(0.85, 0.43, 0.48)	(0.74, 0.35, 0.27)	(0.86, 0.45, 0.12)	(0.32, 0.25, 0.43)	(0.79, 0.49, 0.16)
	A	(0.66, 0.25, 0.09)	(0.88, 0.44, 0.44)	(0.58, 0.27, 0.15)	(0.46, 0.12, 0.42)	(0.82, 0.43, 0.5)	(0.9, 0.32, 0.41)
	N	(0.87, 0.44, 0.2)	(0.57, 0.15, 0.28)	(0.87, 0.34, 0.19)	(0.7, 0.35, 0.24)	(0.37, 0.37, 0.26)	(0.61, 0.41, 0.31)
A6	H	(0.81, 0.32, 0.32)	(0.83, 0.26, 0.15)	(0.32, 0.4, 0.28)	(0.67, 0.38, 0.19)	(0.38, 0.11, 0.51)	(0.51, 0.34, 0.15)
	A	(0.54, 0.27, 0.19)	(0.84, 0.24, 0.31)	(0.77, 0.26, 0.35)	(0.82, 0.48, 0.16)	(0.86, 0.3, 0.2)	(0.58, 0.49, 0.3)
	N	(0.5, 0.35, 0.15)	(0.44, 0.13, 0.43)	(0.38, 0.15, 0.47)	(0.39, 0.16, 0.45)	(0.68, 0.17, 0.15)	(0.51, 0.46, 0.03)
A7	H	(0.58, 0.37, 0.05)	(0.4, 0.18, 0.42)	(0.32, 0.17, 0.51)	(0.47, 0.17, 0.36)	(0.35, 0.15, 0.5)	(0.58, 0.18, 0.24)
	A	(0.52, 0.3, 0.18)	(0.71, 0.12, 0.17)	(0.78, 0.35, 0.13)	(0.82, 0.47, 0.12)	(0.47, 0.42, 0.11)	(0.75, 0.17, 0.08)
	N	(0.43, 0.25, 0.32)	(0.59, 0.35, 0.06)	(0.52, 0.29, 0.19)	(0.75, 0.11, 0.14)	(0.45, 0.39, 0.16)	(0.84, 0.3, 0.31)
A8	H	(0.36, 0.28, 0.36)	(0.62, 0.2, 0.18)	(0.46, 0.25, 0.29)	(0.31, 0.23, 0.46)	(0.43, 0.23, 0.34)	(0.37, 0.46, 0.17)
	A	(0.66, 0.37, 0.42)	(0.6, 0.13, 0.27)	(0.62, 0.33, 0.05)	(0.75, 0.27, 0.15)	(0.47, 0.25, 0.28)	(0.69, 0.33, 0.24)
	N	(0.89, 0.34, 0.19)	(0.36, 0.16, 0.48)	(0.45, 0.16, 0.39)	(0.41, 0.21, 0.38)	(0.4, 0.46, 0.14)	(0.35, 0.31, 0.34)

Table 4. Evaluation of volleyball team based on expert 3 assessments.

Strategy	**Q**	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**
A1	H	(0.55, 0.49, 0.14)	(0.54, 0.49, 0.45)	(0.79, 0.2, 0.01)	(0.4, 0.37, 0.23)	(0.86, 0.32, 0.33)	(0.47, 0.41, 0.12)
	A	(0.41, 0.23, 0.36)	(0.56, 0.3, 0.14)	(0.45, 0.15, 0.4)	(0.67, 0.22, 0.11)	(0.65, 0.16, 0.19)	(0.59, 0.31, 0.1)
	N	(0.33, 0.23, 0.44)	(0.38, 0.13, 0.49)	(0.89, 0.23, 0.42)	(0.45, 0.37, 0.18)	(0.76, 0.34, 0.29)	(0.55, 0.24, 0.21)
A2	H	(0.86, 0.43, 0.49)	(0.37, 0.39, 0.24)	(0.86, 0.17, 0.13)	(0.74, 0.33, 0.44)	(0.38, 0.42, 0.2)	(0.42, 0.17, 0.41)
	A	(0.4, 0.43, 0.17)	(0.7, 0.31, 0.24)	(0.83, 0.26, 0.43)	(0.56, 0.25, 0.19)	(0.58, 0.22, 0.2)	(0.75, 0.3, 0.19)
	N	(0.84, 0.25, 0.32)	(0.84, 0.35, 0.15)	(0.86, 0.35, 0.23)	(0.38, 0.42, 0.2)	(0.67, 0.31, 0.02)	(0.84, 0.42, 0.16)
A3	H	(0.49, 0.2, 0.31)	(0.75, 0.11, 0.14)	(0.64, 0.4, 0.45)	(0.51, 0.43, 0.06)	(0.37, 0.44, 0.19)	(0.38, 0.26, 0.36)
	A	(0.78, 0.16, 0.06)	(0.44, 0.39, 0.17)	(0.73, 0.36, 0.38)	(0.63, 0.2, 0.17)	(0.51, 0.17, 0.32)	(0.85, 0.33, 0.26)
	N	(0.58, 0.48, 0.16)	(0.65, 0.3, 0.05)	(0.67, 0.11, 0.22)	(0.82, 0.47, 0.33)	(0.72, 0.47, 0.38)	(0.39, 0.33, 0.28)
A4	H	(0.66, 0.27, 0.07)	(0.74, 0.47, 0.47)	(0.57, 0.15, 0.28)	(0.89, 0.44, 0.15)	(0.85, 0.45, 0.31)	(0.65, 0.26, 0.09)
	A	(0.33, 0.23, 0.44)	(0.78, 0.1, 0.12)	(0.5, 0.26, 0.24)	(0.62, 0.47, 0.24)	(0.51, 0.4, 0.09)	(0.57, 0.19, 0.24)
	N	(0.57, 0.16, 0.27)	(0.41, 0.3, 0.29)	(0.55, 0.47, 0.24)	(0.65, 0.35, 0.0)	(0.31, 0.37, 0.32)	(0.41, 0.48, 0.11)
A5	H	(0.39, 0.27, 0.34)	(0.35, 0.5, 0.15)	(0.6, 0.34, 0.06)	(0.34, 0.4, 0.26)	(0.43, 0.46, 0.11)	(0.42, 0.18, 0.4)
	A	(0.32, 0.29, 0.39)	(0.64, 0.13, 0.23)	(0.77, 0.28, 0.31)	(0.56, 0.26, 0.18)	(0.64, 0.16, 0.2)	(0.41, 0.44, 0.15)
	N	(0.87, 0.25, 0.21)	(0.69, 0.26, 0.05)	(0.32, 0.16, 0.52)	(0.73, 0.36, 0.11)	(0.43, 0.19, 0.38)	(0.7, 0.11, 0.19)
A6	H	(0.36, 0.42, 0.22)	(0.41, 0.36, 0.23)	(0.44, 0.14, 0.42)	(0.45, 0.39, 0.16)	(0.81, 0.43, 0.26)	(0.7, 0.18, 0.12)
	A	(0.48, 0.46, 0.06)	(0.31, 0.13, 0.56)	(0.42, 0.11, 0.47)	(0.41, 0.33, 0.26)	(0.55, 0.46, 0.43)	(0.51, 0.2, 0.29)
	N	(0.53, 0.34, 0.13)	(0.46, 0.35, 0.19)	(0.55, 0.32, 0.13)	(0.56, 0.22, 0.22)	(0.87, 0.41, 0.16)	(0.82, 0.29, 0.46)
A7	H	(0.78, 0.27, 0.11)	(0.46, 0.32, 0.22)	(0.68, 0.2, 0.12)	(0.38, 0.43, 0.19)	(0.89, 0.31, 0.17)	(0.46, 0.11, 0.43)
	A	(0.85, 0.15, 0.0)	(0.65, 0.21, 0.14)	(0.63, 0.36, 0.01)	(0.8, 0.18, 0.02)	(0.31, 0.15, 0.54)	(0.84, 0.45, 0.34)
	N	(0.66, 0.37, 0.17)	(0.85, 0.27, 0.25)	(0.61, 0.12, 0.27)	(0.4, 0.4, 0.2)	(0.35, 0.34, 0.31)	(0.45, 0.26, 0.29)

A8	H	(0.47, 0.24, 0.29)	(0.73, 0.22, 0.05)	(0.64, 0.29, 0.07)	(0.7, 0.47, 0.39)	(0.43, 0.11, 0.46)	(0.46, 0.34, 0.2)
	A	(0.33, 0.3, 0.37)	(0.66, 0.23, 0.11)	(0.76, 0.14, 0.1)	(0.35, 0.39, 0.26)	(0.6, 0.38, 0.02)	(0.56, 0.2, 0.24)
	N	(0.79, 0.42, 0.38)	(0.46, 0.34, 0.2)	(0.52, 0.14, 0.34)	(0.85, 0.15, 0.0)	(0.87, 0.28, 0.17)	(0.63, 0.45, 0.39)

5. Results & Discussion

This section presents the findings of the proposed approach for opponent analysis and strategy selection framework applied to college volleyball. The results are analyzed based on the case study described in the previous section. The discussion focuses on interpreting the results, comparing the selected strategy with traditional DM approaches, and examining the practical implications of our approach in real-world volleyball coaching.

The results of applying the proposed CWAO scheme to various QNSS decision matrices provided by different volleyball experts are shown in Tables 5-7. These tables showcase the aggregated QNSS components for each strategy A_i across the criteria C_1 *to* C_6, considering the varying contexts. The aggregation process employs the CWAO, which syndicated hybrid weighted geometric averaging to guarantee a balanced and robust capturing of the relative importance of each context. The results highlighted the suitablity of each strategy under various criteria, which provide a inclusive and nuanced DM for optimizing the defensive strategy against a strong attacking opponent.

Table 5: Context-Aware Aggregation Results for QNSS Decision Matrix from Expert 1.

Strategy	C1	C2	C3	C4	C5	C6
A1	(0.449, 0.320, 0.230)	(0.614, 0.257, 0.197)	(0.534, 0.170, 0.293)	(0.603, 0.327, 0.243)	(0.554, 0.387, 0.230)	(0.572, 0.320, 0.103)
A2	(0.677, 0.207, 0.283)	(0.607, 0.233, 0.313)	(0.493, 0.287, 0.360)	(0.573, 0.303, 0.290)	(0.585, 0.217, 0.277)	(0.618, 0.340, 0.290)
A3	(0.564, 0.223, 0.207)	(0.456, 0.163, 0.380)	(0.570, 0.307, 0.330)	(0.672, 0.367, 0.183)	(0.600, 0.390, 0.287)	(0.673, 0.317, 0.200)
A4	(0.648, 0.240, 0.160)	(0.684, 0.469, 0.167)	(0.620, 0.300, 0.177)	(0.543, 0.170, 0.283)	(0.605, 0.377, 0.120)	(0.390, 0.317, 0.293)
A5	(0.607, 0.190, 0.280)	(0.476, 0.423, 0.317)	(0.677, 0.223, 0.223)	(0.593, 0.323, 0.217)	(0.591, 0.137, 0.263)	(0.627, 0.360, 0.220)
A6	(0.430, 0.160, 0.410)	(0.583, 0.347, 0.187)	(0.602, 0.439, 0.220)	(0.543, 0.253, 0.333)	(0.680, 0.310, 0.327)	(0.647, 0.386, 0.183)
A7	(0.585, 0.320, 0.200)	(0.536, 0.233, 0.227)	(0.643, 0.413, 0.317)	(0.567, 0.260, 0.167)	(0.585, 0.323, 0.370)	(0.674, 0.383, 0.263)
A8	(0.511, 0.390, 0.167)	(0.581, 0.187, 0.360)	(0.583, 0.313, 0.330)	(0.555, 0.307, 0.133)	(0.479, 0.280, 0.420)	(0.482, 0.310, 0.333)

Table 6: Context-Aware Aggregation Results for QNSS Decision Matrix from Expert 2.

Strategy	C1	C2	C3	C4	C5	C6
A1	(0.684, 0.357, 0.377)	(0.532, 0.203, 0.313)	(0.540, 0.130, 0.327)	(0.521, 0.370, 0.260)	(0.512, 0.313, 0.220)	(0.619, 0.260, 0.107)
A2	(0.603, 0.240, 0.147)	(0.566, 0.330, 0.100)	(0.643, 0.400, 0.273)	(0.668, 0.227, 0.157)	(0.599, 0.307, 0.277)	(0.583, 0.443, 0.150)
A3	(0.609, 0.350, 0.230)	(0.347, 0.380, 0.273)	(0.560, 0.240, 0.197)	(0.579, 0.363, 0.140)	(0.495, 0.170, 0.333)	(0.668, 0.317, 0.310)
A4	(0.550, 0.287, 0.243)	(0.571, 0.393, 0.313)	(0.662, 0.320, 0.217)	(0.609, 0.337, 0.370)	(0.509, 0.360, 0.323)	(0.561, 0.449, 0.190)
A5	(0.679, 0.287, 0.137)	(0.689, 0.340, 0.400)	(0.678, 0.320, 0.203)	(0.652, 0.307, 0.260)	(0.502, 0.350, 0.396)	(0.685, 0.406, 0.293)
A6	(0.606, 0.313, 0.220)	(0.674, 0.210, 0.297)	(0.489, 0.270, 0.367)	(0.617, 0.340, 0.267)	(0.629, 0.193, 0.287)	(0.530, 0.430, 0.160)
A7	(0.508, 0.307, 0.183)	(0.562, 0.217, 0.217)	(0.538, 0.270, 0.277)	(0.656, 0.250, 0.207)	(0.423, 0.320, 0.257)	(0.675, 0.217, 0.210)

A8	(0.627, 0.330, 0.323)	(0.524, 0.163, 0.310)	(0.508, 0.247, 0.243)	(0.489, 0.237, 0.330)	(0.433, 0.313, 0.253)	(0.469, 0.367, 0.250)

Table 7: Context-Aware Aggregation Results for QNSS Decision Matrix from Expert 3.

Strategy	**C1**	**C2**	**C3**	**C4**	**C5**	**C6**
A1	(0.430, 0.317, 0.313)	(0.492, 0.307, 0.360)	(0.678, 0.193, 0.277)	(0.505, 0.320, 0.173)	(0.680, 0.273, 0.270)	(0.533, 0.320, 0.143)
A2	(0.676, 0.370, 0.327)	(0.626, 0.350, 0.210)	(0.619, 0.260, 0.263)	(0.556, 0.333, 0.277)	(0.540, 0.317, 0.140)	(0.651, 0.297, 0.253)
A3	(0.606, 0.280, 0.177)	(0.603, 0.267, 0.120)	(0.649, 0.290, 0.350)	(0.635, 0.367, 0.187)	(0.531, 0.360, 0.297)	(0.538, 0.307, 0.300)
A4	(0.518, 0.220, 0.260)	(0.630, 0.290, 0.293)	(0.536, 0.293, 0.253)	(0.674, 0.420, 0.130)	(0.554, 0.406, 0.240)	(0.540, 0.310, 0.147)
A5	(0.525, 0.270, 0.313)	(0.556, 0.297, 0.143)	(0.560, 0.260, 0.297)	(0.541, 0.340, 0.183)	(0.498, 0.270, 0.230)	(0.508, 0.243, 0.247)
A6	(0.456, 0.406, 0.137)	(0.393, 0.280, 0.327)	(0.469, 0.190, 0.340)	(0.472, 0.313, 0.213)	(0.685, 0.433, 0.283)	(0.652, 0.223, 0.290)
A7	(0.680, 0.263, 0.093)	(0.637, 0.267, 0.203)	(0.622, 0.227, 0.133)	(0.525, 0.337, 0.137)	(0.516, 0.267, 0.340)	(0.578, 0.273, 0.353)
A8	(0.528, 0.320, 0.347)	(0.606, 0.263, 0.120)	(0.624, 0.190, 0.170)	(0.624, 0.337, 0.217)	(0.622, 0.257, 0.217)	(0.546, 0.330, 0.277)

Following the derivation of the final aggregation matrix based on the CWAO, we compute the weights of different criteria in Figure 1.

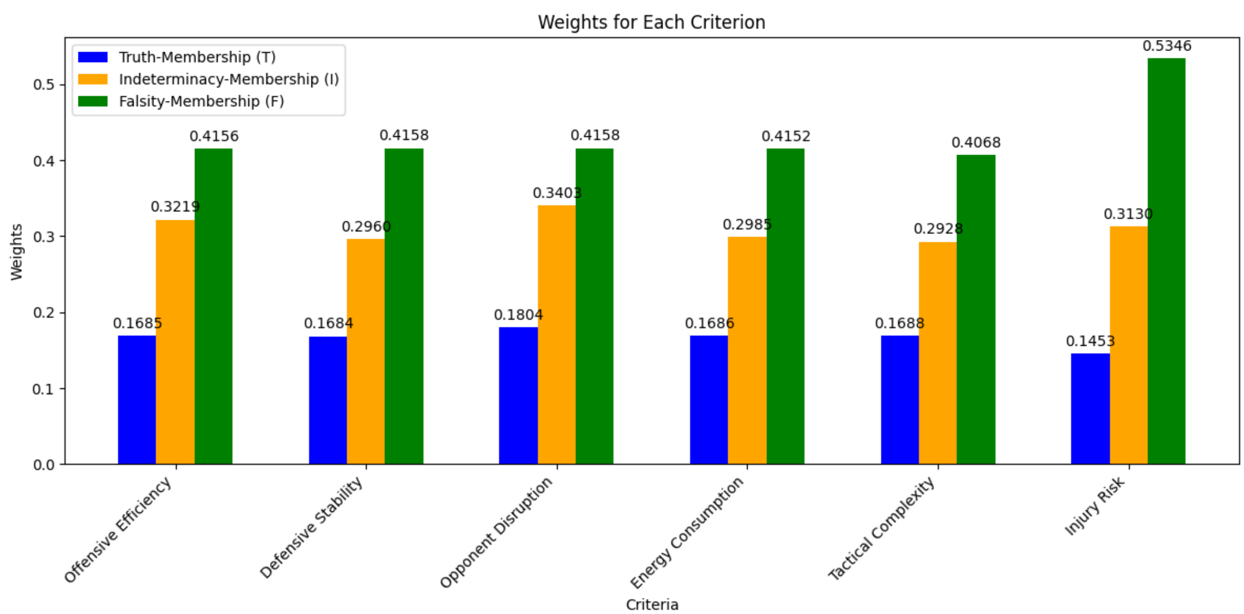

Figure 1. Visualization of computed weights for different criteria in terms of components of the aggregated QNSS.

To assess the competitiveness of the proposed approach against conventional DM approaches (fuzzy COPRA [14], Fuzzy OCRA [15], Fuzzy Edas [16]) , we provide a summary of results of comparative analysis in Table 8. It can be noted that our model outperforms previous methods in handling highly uncertain, vague, as well as incomplete information inherent in volleyball analysis. The fuzzy COPRA, while effective in dealing with uncertainty to some extent, lacks the indeterminate component needed to capture real-world ambiguity fully. In similar way, Fuzzy

OCRA, though mathematically robust, require well-defined probability distributionss. The QNSS approach, by contrast, show a great evidence on more flexible and comprehensive framework by integration multi-context components, which lead to more robust and adaptable DM.

Table 8. Comparative analysis of our approach against different methods.

Method	
Our	A1> A2> A5> A4> A6> A8> A3> A7
Fuzzy COPRA [14]	A1> A2> A5> A4> A8> A6> A7> A3
Fuzzy Edas [16]	A1> A2> A4> A5 > A8> A7> A6> A3
Fuzzy OCRA [15]	A1> A2> A6> A4 > A5 > A8> A3> A7

To further validate the reliability of our approach model, we performed a sensitivity analysis to assess how variations in uncertainty levels impact opponent analysis (Table 9.). Sensitivity analysis is crucial in evaluating whether small perturbations in weights lead to significant changes in output, which ensured that the model remains stable and practical under dynamic startup environments.

Table 9. Sensitivity Analysis of our approach

Weight Adjustment	Rank
-40%	A1> A2> A5> A4> A6> A8> A3> A7
-30%	A1> A2> A5> A4> A6> A8> A3> A7
-10%	A1> A2> A5> A4> A6> A8> A3> A7
+40%	A1> A2> A5> A4> A6> A8> A3> A7
+30%	A1> A2> A5> A4> A6> A8> A3> A7
+10%	A1> A2> A5> A4> A6> A8> A3> A7

6. Conclusion

This study research investigates a Q-Neutrosophic Soft Set (QNSS) approach for managing uncertainty in opponent analysis and game strategy DM in college volleyball. Our framework proposes a multi-context aggregation operator for generating insightful and multi-dimension decision matrix. Then, the aggregated QNSS is then used to develop a customized Best-Worst Method to rate the contribution or importance of different parameters for different DM analysis. Our approach was applied to realistic case study for opponent analysis in college volleyball, which demonstrated its practicality in sports strategy formulation under multi-context, and multi-factor scenarios. Future research will extend this framework to integrate dynamic optimization methods to solve complex sports DM problems.

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