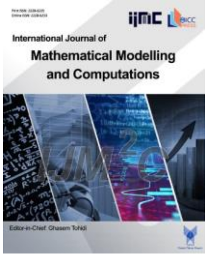

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Research Article

A Hybrid Nonlinear-OWA Framework for Comprehensive Risk Assessment in Dam Construction: Evidence from the Gotvand Case Study

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Abstract

Large dam projects pose multifaceted risks spanning environmental, biological, health, and security domains. Conventional multi-criteria decision-making (MCDM) methods often suffer from two critical limitations: fixed or subjective weighting schemes and rigid aggregation rules that cannot capture decision-makers' optimism or pessimism. This study introduces a novel hybrid framework that integrates a nonlinear optimization model with the Ordered Weighted Averaging (OWA) operator under the minimax disparity approach. The nonlinear model ensures fairness in weighting by deriving closed-form solutions that prevent dominance by individual criteria, while the OWA operator provides flexibility by explicitly incorporating the decision-maker's attitude through the orness parameter. The framework is applied to the Gotvand Dam in Iran, where 19 risk indicators across four categories were evaluated using expert surveys. Results highlight that ecological and health-related risks, such as pest breeding, vegetation change, and biodiversity threats, consistently rank above structural and security hazards. Importantly, rankings remain stable across moderate optimism levels ($\alpha = 0.55$-0.65) but change at higher optimism ($\alpha = 0.70$), demonstrating both robustness and sensitivity to stakeholder perspectives. The main contribution of this work lies in combining analytical tractability with decision-making flexibility, offering a mathematically rigorous yet practical tool for dam risk governance. The findings not only shift attention toward long-term ecological and public health risks but also provide a generalizable framework for large-scale infrastructure risk assessment.

Keywords: Dam risk assessment; Multi-criteria decision-making (MCDM); Ordered weighted averaging (OWA); Nonlinear optimization; Environmental and ecological risks

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1. Introduction

Risk identification, assessment, and control form an integrated and sequential process at the core of modern risk management. This cycle requires careful planning, effective management, and a structured feedback mechanism. In the context of occupational health and safety (OHS), it is applied as a systematic approach for detecting and evaluating both existing and potential risks in the workplace, followed by the implementation of measures to reduce or control their impacts to an acceptable level [1]. Organizations that implement this process effectively are better positioned to recognize risks associated with tasks, the working environment, and employees, thereby achieving positive outcomes. This approach enables managers to identify and address unsafe procedures that violate standards or could lead to fatalities, injuries, or material losses by introducing preventive and corrective actions. Importantly, the process must be conducted periodically and revised in line with the philosophy of continuous improvement to ensure that risk controls remain relevant and effective over time.

A wide range of methodologies has been proposed for risk assessment and control across various industries, from manufacturing to defense [2]. Among these, dam construction represents a particularly critical sector, as construction sites in this domain are often exposed to diverse and complex risks [3]. Hence, there is a strong need for innovative, sector-specific approaches that address the shortcomings of traditional methods and transform them into practical strengths.

The most widely used classical approaches in OHS risk assessment include the decision matrix method (commonly referred to as the 5 × 5 matrix or L-matrix), the Fine-Kinney method, event tree analysis (ETA), operability studies (HAZOP), failure modes and effects analysis (FMEA), preliminary risk analysis (PRA), fault tree analysis (FTA), and multi-criteria decision analysis (MCDA) [2,4,5]. Despite their popularity, these methods have significant limitations. For instance, the decision matrix method does not assign differentiated weights to severity and probability parameters, while its reliance on a subjective 1-5 scale makes precise evaluation difficult [6–8]. Similarly, the Fine-Kinney method applies equal weighting to probability, frequency, and severity, which may not adequately reflect the actual importance of each parameter [9].

Despite progress, existing approaches generally rely on subjective weighting, oversimplified scales, or fuzzy extensions that require iterative processes. They lack analytical transparency and often fail to explicitly account for the decision-maker's attitude toward optimism or pessimism in the aggregation process. Particularly in the context of dam construction, there is limited research that integrates mathematically rigorous weighting with flexible aggregation to comprehensively evaluate diverse categories of risks. To address this gap, the present study introduces a hybrid framework that combines a nonlinear optimization model with the Ordered Weighted Averaging (OWA) operator under the minimax disparity approach. The nonlinear model ensures fairness and transparency by producing closed-form weights proportional to observed data, while the OWA operator incorporates the decision-maker's optimism level through the orness parameter. This integration provides both robustness and adaptability, enabling systematic prioritization of physicochemical, biological, health and safety, and security risks in dam construction. The Gotvand Dam case study demonstrates the applicability of this approach and highlights its ability to capture both stable and sensitivity-dependent aspects of risk prioritization.

The remainder of this paper is organized as follows. Section 2 provides a review of related literature on dam risk assessment and multi-criteria decision-making approaches. Section 3 describes the proposed methodology, including the nonlinear optimization model and the OWA operator with minimax disparity weights. Section 4 presents the case study of the Gotvand Dam, detailing the data collection process and the identified risk indicators. This section reports the results of the nonlinear model and OWA rankings, followed by a comprehensive discussion of their implications, as well. Finally, Section 5 concludes the study by summarizing the key findings, outlining the advantages and limitations of the proposed framework, managerial implications and suggesting directions for future research.

2. Literature review

The primary purposes of dam construction projects include providing water for domestic, agricultural, and industrial uses, flood control, and electricity generation [10]. Unlike conventional construction projects, dams are associated with a wider variety of risks due to their scale, complexity, and the long-term consequences of potential failures. Consequently, risk management in dam projects is more demanding, and standard occupational health and safety (OHS) practices may not sufficiently mitigate the unique risks encountered. For this reason, systematic numerical evaluation and prioritization of risks, are essential in effective dam risk analysis.

The academic literature provides numerous studies addressing risk in dam construction and operation through multi-criteria decision-making (MCDM) techniques. For instance, Samaras et al. [11] applied the Analytic Hierarchy Process (AHP) and the ELECTRE I method for evaluating risks in earth-fill dams. Similarly, Ribas and Pérez-Díaz [12] employed fuzzy approximate reasoning in dam safety assessment, using fuzzy AHP to weight indicators and demonstrating applicability through a hydroelectric plant case in Brazil. In Iran, Sadeh and Rezaian [13] implemented TOPSIS and RAM-D to analyze 43 different risk factors, identifying erosion and its intensification as the highest-priority concerns, followed by excavation, embankment, tunnels, and road-building activities. Darvishi et al. [14] evaluated construction-phase risks using environmental failure mode and effect analysis (FMEA) combined with the VIKOR method. Bid and Siddique [15] conducted a risk assessment of dams in India with TOPSIS and WASPAS, while Chen et al. [16] proposed a probabilistic triplet model under grey–stochastic–fuzzy uncertainty for roller-compacted concrete dams. Yucesan and Kahraman [17] assessed hydropower dam risks using the Pythagorean fuzzy AHP approach. More recently, Beiranvand [18] introduced a modified fuzzy FMEA integrated with fuzzy OWA to evaluate environmental risks of earth dams, emphasizing the role of flexible aggregation operators in capturing uncertainty. Similarly, Fu et al. [19] developed a game-theoretic performance measure for water resources management, highlighting the potential of hybrid models that combine optimization and MCDM. In a related domain, Moradi et al. [20] explored trade-off and orness space in OWA operators for land-use decision-making, providing a theoretical foundation for attitude-sensitive aggregation that is highly relevant to dam risk contexts.

The above literature demonstrates a strong emphasis on employing MCDM methods in dam safety and construction risk assessment, frequently incorporating fuzzy set extensions to handle uncertainty. However, most prior studies either rely on subjective weighting or employ fuzzy frameworks that require iterative procedures, limiting analytical transparency. In contrast, the present study distinguishes itself by proposing an integrated framework that combines a closed-form nonlinear optimization model for deriving fair and transparent weights with the OWA operator, which introduces an adjustable aggregation mechanism reflecting both optimistic and pessimistic perspectives in dam-related risk assessment.

3. Methodology

The methodology of this study is structured around a two-part framework designed to ensure both analytical rigor and decision-making flexibility in dam risk assessment. In the first part, a nonlinear optimization model is developed to derive fair and transparent weights for the identified risk indicators. This model generates closed-form solutions that prevent dominance by a single criterion and provide a robust intensity measure of each risk. In the second part, the OWA operator is employed under the minimax disparity approach. The OWA framework enables explicit modeling of the decision-maker's attitude through the orness parameter, allowing risk prioritization to reflect varying levels of optimism or pessimism. By integrating these two components, the proposed methodology combines the strengths of optimization-based weighting and attitude-sensitive aggregation, offering a comprehensive and adaptable tool for evaluating complex risks in dam construction projects.

3.1. Optimization Results for Dam Risk Factors

In this study, the ranking of dam-related risks was approached through a nonlinear optimization model. For each risk indicator c_{ij}, the objective function is formulated as:

$$\max \ z = cw$$

$$s.t. \ \sum_{k=1}^{n} w_k^2 = 1, \tag{1}$$

$$w_k \geq 0, \quad k = 1, 2, \ldots, n$$

where $c = (c_1, c_2, \ldots, c_n)$ denotes the coefficients corresponding to the risk scores, and $w = (w_1, w_2, \ldots, w_n)^t$ represents the decision weights. The constraint $\sum w_k^2 = 1$ ensures that the weights lie on the surface of the unit hypersphere, while the non-negativity condition guarantees meaningful interpretations in the context of risk assessment.

Solution Approach

This model can be solved analytically using Lagrangian multipliers. The Lagrangian is

$$L(w,\lambda) = c^\top w - \lambda\left(\sum_{k=1}^{n} w_k^2 - 1\right).$$

Setting the derivative with respect to w to zero yields:

$$\frac{\partial L}{\partial w_k} = c_k - 2\lambda w_k = 0 \Rightarrow w_k = \frac{c_k}{2\lambda}$$

Substituting into the constraint $\sum w_k^2 = 1$ leads to

$$\sum_{k=1}^{n} \left(\frac{c_k}{2\lambda}\right)^2 = 1 \Rightarrow \lambda = \frac{1}{2} \parallel c \parallel_2$$

Thus, the optimal solution is obtained directly as:

$$w^\star = \frac{c}{\parallel c \parallel_2}, z^\star = \parallel c \parallel_2,$$

Where $\parallel c \parallel_2 = \sqrt{\sum c_k^2}$ is the Euclidean norm of vector c. The nonlinear optimization model employed in this study offers several distinct advantages for multi-criteria risk assessment. First, it provides a closed-form analytical solution, eliminating the need for iterative algorithms and ensuring computational efficiency even when dealing with large datasets. By normalizing weights with respect to the Euclidean norm, the model achieves a fair distribution that prevents dominance by any single parameter and guarantees proportional contribution of all coefficients to the final score. The model is also robust, as scaling all coefficients by a constant alters only the magnitude of the optimal value without affecting the ranking of alternatives. In addition, the method is highly interpretable: the optimal objective value corresponds directly to the Euclidean length of the coefficient vector, serving as a clear and intuitive measure of overall risk intensity. Finally, unlike simple averaging or weighted-sum approaches, the nonlinear model explicitly balances multiple criteria within a mathematically rigorous framework, making it particularly well suited to complex multi-criteria decision-making.

3.2. OWA operator

The OWA operator was originally introduced by Yager [21] for use in multi-criteria decision-making problems. Considering an alternative $x = (x_1, \ldots, x_n)$, the OWA score is computed as $F(x) = \sum_{i=1}^{n} w_i y_i$, where y_i represents the i-th largest element of the vector x, and $w = (w_1, \ldots, w_n)$ is the vector of weights. The weights must satisfy the basic constraints of non-negativity and unit summation.

$$\sum_{k=1}^{n} (n-k) w_k = (n-1)\alpha$$

$$\sum_{k=1}^{n} w_k = 1 \qquad (2)$$

$$w_k \geq 0, \qquad k = 1,2,\dots,n$$

The orness parameter $\alpha \in [0,1]$ is used to express the degree of optimism of the decision-maker in the OWA operator. For any alternative x, the OWA aggregation yields a score that ranges between two extremes: a completely pessimistic case when $\alpha = 0$, and a completely optimistic case when $\alpha = 1$. In the extreme case of a fully pessimistic decision-maker, the OWA weights are set as $w = (0,0,\dots,1)$. Under this configuration, the OWA score for an alternative $x = (x_1,\dots,x_n)$ becomes $F(x) = y_n = \min\{x_i : i = 1,\dots,n\}$, which corresponds to choosing the smallest component of the vector. Conversely, for a fully optimistic decision-maker, the weights are defined as $w = (1,0,\dots,0)$. In this situation, the OWA score reduces to $F(x) = y_1 = \max\{x_i : i = 1,\dots,n\}$, that is, the highest value among the set of criteria is taken. In this situation, the decision-maker places complete emphasis on the most significant element of the vector x. Consequently, the OWA score spans a continuum between two extremes: the fully pessimistic and the fully optimistic perspectives. In general, higher values of α correspond to aggregation scenarios where an optimistic decision-maker assigns greater importance to the largest components. Conversely, lower values of α reflect a pessimistic stance, where more weight is allocated to the least significant values. Additional properties and characteristics of the OWA operator have been discussed extensively in the literature [22-23]. To operationalize the OWA, a systematic procedure for determining the weights is required, and numerous methods for weight generation have been proposed in the existing body of research.

The earliest linear programming (LP) approach proposed for the determination of OWA weights is referred to as the minimax disparity model, originally introduced by Wang and Parkan [24]. This model, which seeks to minimize the maximum disparity among assigned weights, can be reformulated in the following disparity model:

$$\text{Min } \delta$$

$$s.t. \sum_{k=1}^{n} (n-k) w_i = (n-1)\alpha$$

$$\sum_{k=1}^{n} w_k = 1 \qquad (3)$$

$$w_k - w_{k+1} \leq \delta, \qquad k = 1,2,\dots,n-1$$

$$w_k - w_{k+1} \geq -\delta, \qquad k = 1,2,\dots,n-1$$

$$w_k \geq 0, \qquad k = 1,2,\dots,n$$

Model (3) is designed to minimize the differences between successive weights as much as possible. For any orness level $\alpha \in (0,1)$ with $\alpha \neq 0.5$, the minimax disparity model can be applied to generate OWA weights suitable for both pessimistic and optimistic decision-making scenarios. In the present study, this model is adopted for weight generation, as it is considered both appropriate for the application and attractive due to its simplicity and ease of implementation.

The OWA operator provides a powerful and flexible mechanism for aggregating multiple risk indicators in dam safety assessment. One of its main advantages is the ability to incorporate the decision-maker's attitude toward risk through the orness parameter, which adjusts the balance between optimistic and pessimistic evaluations [25]. This feature ensures that the aggregation process is not fixed but can reflect varying managerial perspectives in real-world decision contexts. In addition, OWA supports a smooth transition between extreme scenarios, from maximum-oriented to minimum-oriented decision rules, thus offering a continuum of aggregation behaviors rather than a single rigid approach. By employing the minimax disparity model to generate weights, OWA also guarantees a fair and evenly distributed weighting scheme that avoids abrupt differences between consecutive weights and enhances consistency in prioritization. Importantly, the operator has been widely adopted in multi-criteria decision-making because it combines mathematical rigor with interpretability, allowing stakeholders to understand how different levels of optimism influence final rankings [26]. In the context of dam construction, where risks are multidimensional and interdependent, OWA's capacity to balance flexibility, fairness, and transparency makes it an invaluable tool for comprehensive risk prioritization.

4. Case study :Gotvand Dam

The development of large dams exerts profound environmental, biological, health-related, social, and economic effects on surrounding ecosystems and communities. With the rapid global expansion of dam construction, evaluating these impacts has become increasingly important. The Gotvand Dam, located in Khuzestan Province, Iran, was initially promoted as one of the country's flagship projects and widely praised for its anticipated environmental and economic benefits as well as its potential for regional development. Over time, however, extensive scientific and technical debate has emerged concerning the risks associated with the dam.

These encompass environmental, security, biological, health, and technical dimensions, with many experts arguing that the risks outweigh the expected ecological and economic advantages. The large number of risks involved, combined with the difficulties of systematically assessing and prioritizing them, has complicated decision-making and hindered timely interventions aimed at prevention and mitigation. Systematic identification, categorization, and prioritization of risks related to the Gotvand Dam are therefore essential inputs for managerial and policy decisions. Ranking these risks provides a clear basis for determining the order of actions required to manage potential crises, thereby supporting more effective risk governance in the region. Despite the stated goals and projected benefits of the dam, evaluations show that, while a limited portion of these objectives has been realized, the project has also generated a wide range of adverse outcomes. Numerous risks have emerged, leading to environmental, security, biological, and health challenges that complicate the development of effective control and mitigation strategies.

Reliable information, together with systematic identification and prioritization of risks, is thus crucial for informed and evidence-based decision-making. Accordingly, this study was designed in several stages to identify, examine, and rank the risks associated with the Gotvand Dam. In the first stage, potential risks were extracted through a comprehensive review of the literature and previous research. Four main categories of risks were established, each defined by specific indicators:

Physicochemical (C1): erosion (C11), salt accumulation (C12), eutrophication (C13), oil spill (C14), soil compaction (C15), and thermal stratification (C16).

Biological (C2): vegetation change (C21), disruption of food chains (C22), threats to animal biodiversity (C23), destruction of aquatic habitats (C24), and barriers to fish migration (C25).

Health and Safety (C3): high noise levels (C31), human error (C32), corrosion of facilities (C33), disease outbreaks (C34), and favorable conditions for pest breeding (C35).

Security (C4): induced earthquakes (C41), threats to human life (C42), and flooding (C43).

To evaluate these risks, a structured questionnaire was developed using pairwise comparison and Likert-scale scoring. Experts from geology, environmental science, civil engineering, and agriculture, each with at least 15 years of professional experience, were invited to participate. In total, 28 experts contributed, including 7 in geology, 6 in civil engineering, 8 in environmental science, and 7 in agriculture. Each risk indicator was rated on a 1-9 scale, where 1 represented "very low importance" and 9 represented "very high importance." The responses were then averaged across experts to derive a consolidated assessment, forming the decision matrix presented in Table 1. In the next stage, a composite score was calculated for each risk indicator. This score was derived using the Simple Additive Weighting (SAW) method, a widely applied technique in MCDM. The procedure involved multiplying the decision matrix values presented in Table 1 by their corresponding weights and summing the results to obtain a single score for each risk. Unlike conventional SAW applications where equal or subjectively assigned weights are often used, in this study the weights of the components were determined objectively through the nonlinear optimization model and the OWA operator. This ensured that the calculated scores reflect both the relative importance of the criteria and the decision-maker's attitude toward optimism or pessimism. The resulting scores were then employed to rank the risks, providing a transparent and rigorous basis for prioritization. For this purpose, the present study employs the nonlinear optimization model described in Section 3.1 to determine the weights of the components. By integrating these optimized weights into the SAW framework, a score is calculated for each risk indicator based on the decision matrix in Table 2. This approach ensures that the resulting scores are not only consistent with multi-criteria decision-making principles but also grounded in an analytically rigorous weighting scheme. The derived scores are subsequently used to rank the risks, thereby providing a transparent and robust foundation for prioritization. Table 2 presents the results of the nonlinear optimization model solved for each risk factor Cij. For each coefficient vector c, the optimal weights w and the maximum objective function value were computed. The risks are ranked from highest to lowest based on their objective function values.

Hybrid computation workflow (summary)

(1) The 4-component decision matrix in Table 1 is first weighted using coefficients obtained from the nonlinear optimization model.

(2) For each risk indicator C_{ij}, the weighted components are summed to obtain a single aggregated score (Table 2).

(3) These aggregated scores form the input vector for the OWA operator.

(4) OWA scores and final rankings are then computed under selected orness levels using the minimax disparity weights (Table 4).

The nonlinear optimization model yielded a clear prioritization of risks associated with the Gotvand Dam (Table 2). The highest-ranked risk was C35 (favorable conditions for pest breeding) with an optimal value of 14.071. This finding underscores the importance of ecological imbalances and their potential to trigger vector-borne diseases, posing long-term threats to both environmental and public health. The second and third positions were occupied by C32 (human error) and C21 (vegetation change), with values of 13.038 and 12.369, respectively. These results highlight the combined significance of operational practices and ecosystem transformations in shaping overall dam safety. Other biological risks, including C23 (threats to animal biodiversity) and C24 (destruction of aquatic habitats), also ranked within the top five, reflecting the predominanc of ecological and biological concerns in

Table 1. Likert-scale decision matrix (components per risk)

Risk	Comp 1	Comp 2	Comp 3	Comp 4
C11	1	3	2	6
C12	5	6	3	3
C13	7	6	4	3
C14	5	5	6	3
C15	4	3	2	3
C16	7	7	5	4
C21	8	8	3	4
C22	4	6	2	4
C23	8	6	4	6
C24	8	6	4	5
C25	5	3	3	5
C31	6	5	5	6
C32	7	7	6	6
C33	6	3	4	6
C34	7	6	5	4
C35	9	7	2	8
C41	4	5	6	6
C42	4	3	6	5
C43	4	5	2	6

the risk landscape of Gotvand Dam. The physicochemical risk C16 (thermal stratification) and the health-related risk C34 (disease outbreaks) followed closely, further emphasizing the strong link between environmental changes in the reservoir and potential health crises. Mid-ranked risks, such as C31 (high noise levels), C41 (induced earthquakes), and C13 (eutrophication), indicate that although their optimal values were lower than the top group, they remain important considerations in dam operation and management. These risks represent a mix of occupational, geophysical, and environmental factors that require ongoing monitoring and mitigation. At the lower end of the ranking, risks such as C22 (disruption of food chains), C25 (barriers to fish migration), C11 (erosion), and C15 (soil compaction) were assigned the smallest optimal values. While these factors may have localized impacts, their relative contribution to overall risk intensity appears less critical compared to biological and health-related issues. As we see, the nonlinear model consistently highlights the dominance of biological and health-related risks over purely structural or physicochemical risks. This pattern suggests that dam risk governance in Gotvand should shift from a narrow engineering perspective toward a broader ecological and social approach. Importantly, the model's closed-form weighting ensures that these rankings are analytically transparent, with the Euclidean norm providing a clear measure of risk intensity.

Now we apply the OWA operator to distinguish further between indicators in each risk. As demonstrated by Wang et al. [24], for any orness value α selected within the interval $0.5 < \alpha < \frac{2n-1}{3(n-1)}$ the corresponding OWA weights remain strictly positive. For the case of $n = 4$ criteria, the orness parameter α may take values within the interval $0.5 < \alpha < 0.777$. Moreover, for any α within this range, every optimal solution of the minimax OWA model (3) satisfies the following inequality structure: $w_1 > w_2 > w_3 > w_4 > 0$. Table 3 presents the OWA weights derived from the minimax model (3) for four selected values of the orness parameter. This table presents the OWA weights obtained from the minimax disparity model for the case of $n = 4$ criteria and selected values of the orness parameter ($\alpha = 0.55, 0.60, 0.65$, and 0.70). In line with prevailing practice in dam risk governance, where decision makers are rarely fully pessimistic or fully optimistic, the orness parameter was varied within a moderately optimistic band $\alpha \in \{0.55, 0.60, 0.65, 0.70\}$. This range (i) excludes the extreme ends of the spectrum, which are seldom adopted in safety-critical decisions, and (ii) remains strictly below the theoretical upper bound $\alpha < 0.777$ for $n = 4$, while approaching it closely enough to reveal whether rank reversals emerge as the OWA profile becomes more top-loaded. The minimax disparity approach minimizes the maximum difference between consecutive weights, leading to a strictly decreasing and smooth weight distribution. This property ensures that the weight profile is balanced while reflecting the optimism level of the decision-maker through α. As α increases, the weights assigned to the higher-ordered inputs (w_1, w_2) increase, while those assigned to the lower-ordered inputs (w_3, w_4) decrease. This shift corresponds to more optimistic aggregation behavior.

The results confirm that the minimax disparity model produces OWA weights that are both interpretable and mathematically consistent. The equal spacing between consecutive weights ($w_1 - w_2 = w_2 - w_3 = w_3 - w_4 = \delta$) demonstrates the disparity minimization property. Furthermore, the weights smoothly transition as α increases, highlighting the model's ability to capture decision-makers' attitudes ranging from moderately balanced to more optimistic scenarios. This makes the approach particularly suitable for multi-criteria risk assessment in dam safety analysis, where fairness in weight distribution and flexibility in reflecting

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subjective attitudes are essential. Figure 1 illustrates how the OWA weights change for $n = 4$ criteria when the orness parameter (α) varies between 0.55 and 0.70. The minimax disparity model ensures that consecutive weights differ by the same amount, leading to a smooth, strictly decreasing distribution. As α increases, the weight vector shifts towards a more optimistic profile: larger weights are allocated to the higher-ordered positions (w_1, w_2), while the weights of the lower-ordered positions (w_3, w_4) decrease accordingly. This demonstrates how the model systematically reflects the decision-maker's attitude toward optimism or pessimism in aggregation.

Next, we present OWA scores and rankings for all risk indicators (Cij) using minimax disparity weights for $n = 4$ at four orness levels $(\alpha = 0.55, 0.60, 0.65, 0.70)$ in Table 4. For each α, the weights are strictly decreasing and evenly spaced, reflecting a smooth shift towards more optimistic aggregation as α increases.

Table 2. Nonlinear optimization results

Rank	Risk	Optimal weights	Optimal value
1	C35	[0.6396, 0.4975, 0.1421, 0.5685]	14.071
2	C32	[0.5369, 0.5369, 0.4602, 0.4602]	13.038
3	C21	[0.6468, 0.6468, 0.2425, 0.3234]	12.369
4	C23	[0.6489, 0.4867, 0.3244, 0.4867]	12.328
5	C24	[0.6737, 0.5053, 0.3369, 0.4211]	11.874
6	C16	[0.5937, 0.5937, 0.4241, 0.3393]	11.789
7	C34	[0.6236, 0.5345, 0.4454, 0.3563]	11.225
8	C31	[0.5432, 0.4527, 0.4527, 0.5432]	11.045
9	C41	[0.3763, 0.4704, 0.5644, 0.5644]	10.630
10	C13	[0.6674, 0.5721, 0.3814, 0.286]	10.488
11	C33	[0.6092, 0.3046, 0.4061, 0.6092]	9.848
12	C14	[0.513, 0.513, 0.6156, 0.3078]	9.746
13	C42	[0.4313, 0.3235, 0.647, 0.5392]	9.273
14	C43	[0.4444, 0.5556, 0.2222, 0.6667]	9.000
15	C12	[0.5625, 0.6751, 0.3375, 0.3375]	8.888
16	C22	[0.4714, 0.7071, 0.2357, 0.4714]	8.485
17	C25	[0.6063, 0.3638, 0.3638, 0.6063]	8.246
18	C11	[0.1414, 0.4243, 0.2828, 0.8485]	7.071
19	C15	[0.6489, 0.4867, 0.3244, 0.4867]	6.164

Table 3. Minimax-OWA weights for selected α ($n = 4$)

α	δ	w_1	w_2	w_3	w_4
0.55	0.03	0.295	0.265	0.235	0.205
0.60	0.06	0.34	0.28	0.22	0.16
0.65	0.09	0.385	0.295	0.205	0.115
0.70	0.12	0.43	0.31	0.19	0.07

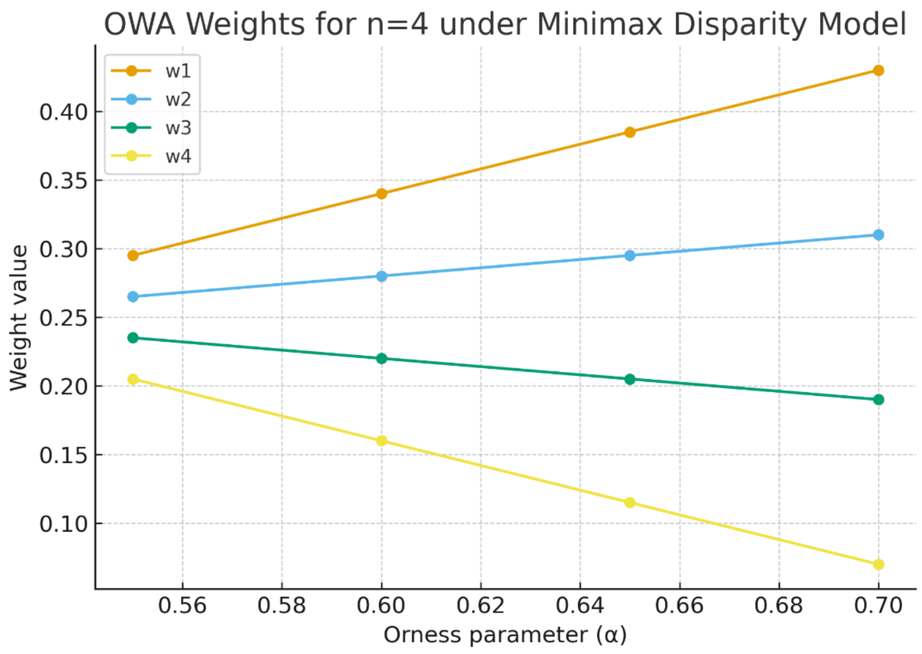

Figure 1. OWA weights for $n = 4$ using the minimax disparity model across selected values of α

Table 4. OWA scores and rankings across α

Risk	OWA Score (α = 0.55)	Rank (α = 0.55)	OWA Score (α = 0.60)	Rank (α = 0.60)	OWA Score (α = 0.65)	Rank (α = 0.65)	OWA Score (α = 0.70)	Rank (α = 0.70)
C35	6.830	1	7.160	1	7.489	1	7.819	1
C32	6.560	2	6.620	2	6.680	2	6.739	3
C23	6.180	3	6.360	3	6.539	4	6.720	4
C21	6.035	4	6.320	4	6.604	3	6.890	2
C24	5.945	5	6.140	5	6.335	5	6.530	5
C16	5.915	6	6.080	6	6.245	6	6.410	6
C34	5.650	7	5.800	7	5.950	7	6.100	7
C31	5.561	8	5.620	8	5.680	8	5.74	9
C41	5.355	9	5.460	9	5.565	10	5.670	10
C13	5.210	10	5.420	10	5.630	9	5.840	8
C33	4.915	11	5.080	11	5.245	11	5.410	11
C14	4.885	12	5.020	12	5.155	12	5.290	12
C42	4.650	13	4.800	13	4.950	13	5.100	13
C43	4.445	14	4.640	14	4.835	14	5.029	14
C12	4.415	15	4.580	15	4.745	15	4.910	15
C22	4.180	16	4.360	16	4.540	16	4.720	16
C25	4.120	17	4.240	17	4.359	17	4.479	17
C11	3.240	18	3.480	18	3.720	18	3.960	18
C15	3.090	19	3.180	19	3.269	19	3.360	19

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OWA scores are computed by sorting each risk's four component values in non-increasing order and applying the corresponding OWA weights.Next, we present OWA scores and rankings for all risk indicators (Cij) using minimax disparity weights for $n = 4$ at four orness levels ($\alpha = 0.55, 0.60, 0.65, 0.70$) in Table 4. For each α, the weights are strictly decreasing and evenly spaced, reflecting a smooth shift towards more optimistic aggregation as α increases. OWA scores are computed by sorting each risk's four component values in non-increasing order and applying the corresponding OWA weights. Now we analyze why the OWA rankings remain identical for $\alpha = 0.55, 0.60$, and 0.65, but differ at $\alpha = 0.70$. Under the minimax disparity model with $n = 4$, the weights are strictly decreasing with equal gaps, leading to stable rankings for moderate α values. However, at $\alpha = 0.70$ the weight vector becomes more top-heavy (greater emphasis on the largest component, reduced emphasis on the smallest), which changes the relative ordering of risks with very similar score profiles. This explains why rank reversals are observed only at $\alpha = 0.70$ (see Table 5 for more details).

As shown in Table 2, C21 (vegetation change) overtakes C32 (human error), while C13 (eutrophication) moves ahead of C31 (high noise). These changes are caused by $\alpha = 0.70$ allocating more weight to the largest component of each risk's profile, favoring those with higher maximum values even if their lower components are weaker.

Figure 2 visualizes the ranking shifts. The stability across $\alpha = 0.55 - 0.65$ demonstrates robustness, while the crossovers at $\alpha = 0.70$ reflect the transition to a more optimistic aggregation regime. This behavior shows that the OWA model provides consistent results under moderate decision-maker optimism, with changes arising only when stronger optimism is imposed.

While the use of 28 experts provided a broad multidisciplinary basis, potential biases related to disciplinary perspective, experience, and subjective judgment cannot be fully eliminated. To assess internal consistency, pairwise correlations among expert ratings were examined, yielding an average $r = 0.74$, indicating substantial agreement. Nevertheless, some variability was observed, reflecting the inherent diversity of viewpoints in dam safety assessment. This variation is valuable, as it captures the multi-dimensional nature of the problem, yet it also highlights the importance of structured elicitation or iterative consensus methods (e.g., Delphi) for future studies.

5. Discussion, conclusion, and managerial implications

This research proposed a hybrid framework for dam risk assessment by combining a nonlinear optimization model with the OWA operator under the minimax disparity approach. Applying the method to the Gotvand Dam provided valuable insights into the prioritization of risks across four main categories: physicochemical, biological, health and safety, and security. The results consistently highlighted that ecological and biological risks, particularly pest breeding, vegetation change, and biodiversity threats, represent the most significant challenges, while physicochemical risks such as eutrophication and salinity accumulation also emerged as critical drivers of environmental degradation. By contrast, structural and security-related risks such as induced earthquakes or flooding received relatively lower ranks, suggesting that their impacts, while important, are either better understood or more readily managed compared to the unpredictable ecological consequences of dam construction and operation.

A notable feature of the findings was the stability of risk rankings under moderate decision-maker optimism, as represented by orness values $\alpha = 0.55, 0.60$, and 0.65. Across this range, the order of priorities remained unchanged, demonstrating the robustness of the approach. However, at α = 0.70, where the OWA weights become more top-heavy and concentrate on the largest component, rank reversals occurred among risks with very similar profiles. This behavior reflects the sensitivity of the method under conditions of strong optimism and highlights the model's ability to capture shifts in attitude. In practical terms, the stability across moderate α values reassure decision-makers of the consistency of results, while the observed changes at higher α underline the flexibility of the OWA framework to represent alternative viewpoints that emphasize best-case scenarios.

The proposed approach offers several advantages. First, it is mathematically rigorous yet computationally efficient, since the nonlinear optimization model admits closed-form solutions that avoid iterative procedures. Second, the method guarantees fairness in weighting: by normalizing the coefficient vectors, it prevents any single criterion from dominating and ensures that evaluations reflect a balanced perspective. Third, the use of the OWA operator introduces flexibility by allowing explicit modeling of the decision-maker's optimism or pessimism. This adaptability is particularly useful in dam safety analysis, where different stakeholders may hold diverging attitudes toward risk.

Table 5. Rank change from α = 0.65 to α = 0.70

Risk	Rank $\alpha = 0.65$	Rank $\alpha = 0.70$	Score $\alpha = 0.65$	Score $\alpha = 0.70$
C32	2	3	6.68	6.74
C21	3	2	6.605	6.89
C31	8	9	5.68	5.74
C13	9	8	5.63	5.84

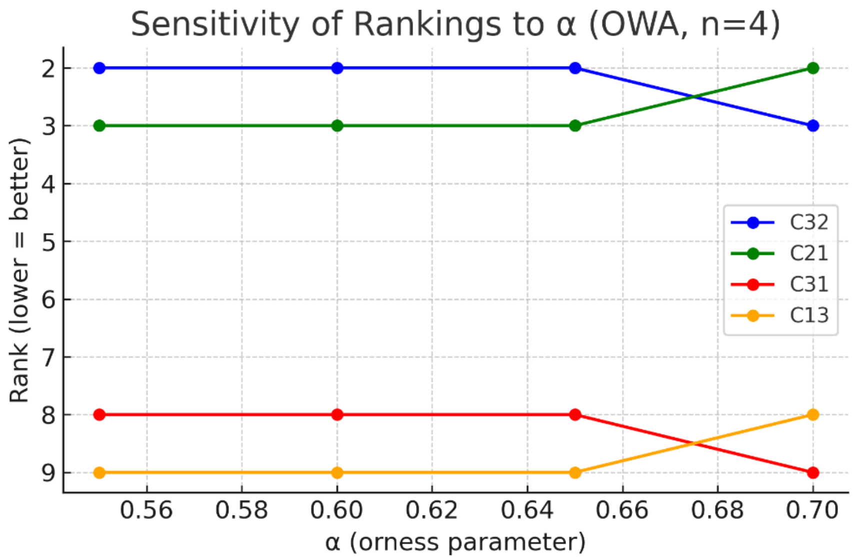

Figure 2. Sensitivity of selected risk rankings to α. Rankings are stable for $\alpha \leq 0.65$ and change only at $\alpha = 0.70$

Fourth, the robustness of rankings under most α values strengthens the reliability of the results. Finally, the integrated framework bridges technical, ecological, and social dimensions, offering a transparent tool to guide managerial and policy decisions. Compared with existing hybrid MCDM frameworks that combine subjective or fuzzy weighting with downstream aggregation (e.g., fuzzy-FMEA-OWA [18], TOPSIS-RAM-D [13], and AHP-ELECTRE [11]), the present method introduces two structural differences. First, the nonlinear model yields closed-form weights that avoid iterative elicitation and reduce opacity arising from expert–driven fuzzification. Second, the OWA stage introduces attitude-controlled aggregation through orness, enabling a transparent sensitivity path from pessimistic to optimistic regimes. Most previous hybrids rely on fixed aggregation rules or do not explicitly expose how decision-maker attitude perturbs rankings. In this study, the observed rank stability for $\alpha \in \{0.55, 0.60, 0.65\}$ and targeted reversals at $\alpha = 0.70$ demonstrate both robustness and controlled sensitivity, a behavioral property not documented in earlier hybrids.

Nonetheless, certain limitations must be acknowledged. The reliance on expert surveys as the primary data source may introduce subjectivity, as responses can be influenced by personal experience and perception. Furthermore, the representation of risks through Likert-scale values simplifies the complexity of real-world uncertainties, potentially overlooking dynamic interactions or temporal variations. The focus on a single case study, namely the Gotvand Dam, limits the generalizability of the findings to other contexts. In addition, the sensitivity of rankings to highly optimistic α values may complicate interpretation in settings where decision-makers differ significantly in their attitudes toward risk.

Looking ahead, future research could address these limitations in several ways. Integrating real-time monitoring data, such as remote sensing of vegetation or automated water quality sensors, would enhance the objectivity of the analysis and reduce reliance on expert judgment. Extending the framework with probabilistic or fuzzy modeling could provide a richer representation of uncertainty and interdependencies. Applying the method to multiple dams in different geographic and socio-economic contexts would help validate its robustness and general applicability. Comparative studies with emerging multi-criteria decision-making techniques such as MARCOS, EDAS, or BWM-IOWA hybrids could further demonstrate the relative strengths of the approach. Finally, developing dynamic OWA models that adjust orness over the lifecycle of a project would offer a more realistic reflection of how stakeholder attitudes evolve as new information becomes available.

The findings of this study carry important implications for dam risk governance. In particular, authorities should prioritize environmental management by mitigating biological and ecological risks through biodiversity conservation programs, vegetation management, and continuous water quality monitoring. Ecological and physicochemical monitoring should be integrated more systematically, as many biological risks are directly driven by water quality changes, making the monitoring of nutrient levels, thermal profiles, and salinity essential. While structural risks such as seismicity and flooding cannot be neglected, the results suggest that ecological risks should be elevated to the same level of strategic importance in decision-making. Furthermore, targeted public health interventions are required to address pest breeding and associated disease outbreaks, necessitating close collaboration with health authorities. In sum, the proposed model highlights pest breeding, vegetation change, biodiversity loss, and water-quality-related risks as the most critical issues for Gotvand Dam. This demonstrates that long-term ecological and public health threats outweigh immediate structural concerns, indicating the need for a paradigm shift in dam risk management, from a primarily engineering-centered focus to a broader environmental and social perspective.

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Authors Contribution
All the authors have participated sufficiently in the intellectual content, conception and design of this work or the analysis and interpretation of the data (when applicable), as well as the writing of the manuscript.

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

Conflict of interests
The author states that there is no conflict of interest.

References

[1] Ahmad, A. C., Zin, I. N. M., Othman, M. K., and Muhamad, N. H. (2016). Hazard Identification, Risk Assessment and Risk Control (HIRARC) Accidents at Power Plant. *MATEC Web Conference*, 66, pp. 00105. DOI: https://doi.org/10.1051/matecconf/20166600105

[2] Gul, M. (2018). A review of occupational health and safety risk assessment approaches based on multi-criteria decision-making methods and their fuzzy versions. *Human and Ecological Risk Assessment*, 24(7), pp. 1723–1760. DOI: https://doi.org/10.1080/10807039.2018.1424531

[3] Rezaian, S., Jozi, S. A., and Zaredar, N. (2016). Environmental risk assessment of a dam during construction phase. *Global Journal of Environmental Science and Management*, 2(4), pp. 345–356. DOI: https://doi.org/10.22034/gjesm.2016.02.04.004

[4] Fattahi, R., Tavakkoli-Moghaddam, R., Khalilzadeh, M., Shahsavari-Pour, N., and Soltani, R. (2020). A novel FMEA model based on fuzzy multiple-criteria decision-making methods for risk assessment. *Journal of Enterprise Information Management*, 33(5), pp. 881–904. DOI: https://doi.org/10.1108/JEIM-09-2019-0282

[5] Marhavilas, P. K., Koulouriotis, D., and Gemeni, V. (2011). Risk analysis and assessment methodologies in the work sites: on a review, classification and comparative study of the scientific literature of the period 2000–2009. *Journal of Loss Prevention in the Process Industries*, 24(5), pp. 477–523. DOI: https://doi.org/10.1016/j.jlp.2011.03.004

[6] Gul, M. and Ak, M. F. (2018). A comparative outline for quantifying risk ratings in occupational health and safety risk assessment. *Journal of Cleaner Production*, 196, pp. 653–664. DOI: https://doi.org/10.1016/j.jclepro.2018.06.106

[7] Oz, N. E., Mete, S., Serin, F., and Gul, M. (2019). Risk assessment for clearing and grading process of a natural gas pipeline project: an extended TOPSIS model with Pythagorean fuzzy sets for prioritizing hazards. *Human and Ecological Risk Assessment*, 25(6), pp. 1615–1632. DOI: https://doi.org/10.1080/10807039.2018.1495057

[8] Oz, N. E., Mete, S., Serin, F., and Gul, M. (2019). Risk assessment for clearing and grading process of a natural gas pipeline project: an extended TOPSIS model with Pythagorean fuzzy sets for prioritizing hazards. *Human and Ecological Risk Assessment*, 25(6), pp. 1615–1632. DOI: https://doi.org/10.1016/j.jsr.2019.03.005

[9] Gul, M., Mete, S., Serin, F., and Celik, E. (2021). Fine–Kinney occupational risk assessment method and its extensions by fuzzy sets: A state-of-the-art review. In: Gul, M., Mete, S., Serin, F., and Celik, E. (eds.) *Fine-Kinney-Based Fuzzy Multi-Criteria Occupational Risk Assessment*. Cham: Springer, pp. 1–11. DOI: https://doi.org/10.1007/978-3-030-52148-6_1

[10] Haghshenas, S. S., Neshaei, M. A. L., Pourkazem, P., and Haghshenas, S. S. (2016). The risk assessment of dam construction projects using fuzzy TOPSIS (case study: Alavian Earth Dam). *Civil Engineering Journal*, 2(4), pp. 158–167. DOI: https://doi.org/10.28991/cej-2016-00000022

[11] Samaras, G. D., Gkanas, N. I., and Vitsa, K. C. (2014). Assessing risk in dam projects using AHP and ELECTRE I. *International Journal of Construction Management*, 14(4), pp. 255–266. DOI: https://doi.org/10.1080/15623599.2014.971942

[12] Ribas, J. R. and Pérez-Díaz, J. I. (2019). A multicriteria fuzzy approximate reasoning approach for risk assessment of dam safety. *Environmental Earth Sciences*, 78(16), article 514. DOI: https://doi.org/10.1007/s12665-019-8526-3

[13] Sadeh, N. and Rezaian, S. (2017). Risk management and control of dams based on integrating TOPSIS and RAM-D Techniques (Case Study: Paveh Rood Dam, Iran). *Environmental Energy and Economic Research*, 1(4), pp. 363–372. DOI: https://doi.org/10.22097/eeer.2018.122552.1024

[14] Darvishi, S., Jozi, S. A., Malmasi, S., and Rezaian, S. (2020). Environmental risk assessment of dams at constructional phase using VIKOR and EFMEA methods (Case study: Balarood Dam, Iran). *Human and Ecological Risk Assessment*, 26(4), pp. 1087–1107. DOI: https://doi.org/10.1080/10807039.2018.1558396

[15] Bid, S. and Siddique, G. (2019). Human risk assessment of Panchet dam in India using TOPSIS and WASPAS multi-criteria decision-making (MCDM) methods. *Heliyon*, 5(6), e01956. DOI: https://doi.org/10.1016/j.heliyon.2019.e01956

[16] Chen, W., Wang, X., Liu, M., Zhu, Y., and Deng, S. (2018). Probabilistic risk assessment of RCC dam considering grey-stochastic-fuzzy uncertainty. *KSCE Journal of Civil Engineering*, 22(11), pp. 4399–4413. DOI: https://doi.org/10.1007/s12205-018-0765-4

[17] Yucesan, M. and Kahraman, G. (2019). Risk evaluation and prevention in hydropower plant operations: a model based on Pythagorean fuzzy AHP. *Energy Policy*, 126, pp. 343–351. DOI: https://doi.org/10.1016/j.enpol.2018.11.039

[18] Beiranvand, B. (2024). Development of modified fuzzy FMEA method in environmental risk assessment of earth dams. *Scientific Reports*, 14(1), article 17585. DOI: https://doi.org/10.1038/s41598-024-68816-7

[19] Fu, Z., Feng, P., and Luo, Z. (2024). Comprehensive assessment of dam safety using a game-theory-based dam safety performance measure. *Water*, 16(5), article 659. DOI: https://doi.org/10.3390/w16050659

[20] Moradi, B., Akbari, R., Taghavi, S. R., Fardad, F., Esmailzadeh, A., Ahmadi, M. Z., et al. (2023). A scenario-based spatial multi-

criteria decision-making system for urban environment quality assessment: case study of Tehran. *Land*, 12(9), article 1659. DOI: https://doi.org/10.3390/land12091659

[21] Yager, R. R. (1988). On ordered weighted averaging aggregation operators in multicriteria decision making. *IEEE Transactions on Systems, Man, and Cybernetics*, 18(1), pp. 183–190. DOI: https://doi.org/10.1109/21.87068

[22] Jin, L., Mesiar, R., and Yager, R. (2019). Ordered weighted averaging aggregation on convex poset. *IEEE Transactions on Fuzzy Systems*, 27(3), pp. 612–617. DOI: https://doi.org/10.1109/TFUZZ.2018.2871957

[23] Yager, R. R. and Alajlan, N. (2014). On characterizing features of OWA aggregation operators. *Fuzzy Optimization and Decision Making*, 13(1), pp. 1–32. DOI: https://doi.org/10.1007/s10700-013-9165-x

[24] Wang, Y. M. and Parkan, C. (2005). A minimax disparity approach for obtaining OWA operator weights. *Information Sciences*, 175(1–2), pp. 20–29. DOI: https://doi.org/10.1016/j.ins.2004.09.005

[25] Tohidi, G. and Khodadadi, M. (2015). The OWA weights of improved minimax disparity model. *International Journal of Intelligent Systems*, 30(7), pp. 781–797.

[26] Khodadadi, M., Tohidi, G., and Zarghami, M. (2017). Sensitivity analysis of the ordered weighted averaging operator via linear models. *Computers & Industrial Engineering*, 112, pp. 264–273.