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Stochastic Sensitivity and Consistency Analysis of Hybrid Wave–Current Energy Concept Selection

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Abstract

Hybrid marine energy systems that integrate wave and current technologies can improve resource complementarity and spatial utilization. However, the ranking stability of selected hybrid concepts under changes in criterion weights, score assumptions, and multi-criteria decision analysis (MCDA) methods requires further examination. This study extends an existing two-stage concept-selection procedure by evaluating four shortlisted wave energy converter–hydrokinetic turbine configurations using stochastic weight-space sampling, criterion-wise weight sensitivity, cross-method consistency, and bounded score-perturbation analyses. A fixed normalized decision matrix is first evaluated using the Simple Additive Weighting (SAW) method across three sets of 10,000 criterion-weight scenarios generated using normalized-uniform, Dirichlet $\alpha = 1$, and Dirichlet $\alpha = 0.5$ distributions. The same scenarios are then evaluated using the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), with ranking consistency quantified using Spearman's rank correlation and complete-ranking agreement. Score sensitivity is subsequently examined through bounded one-point perturbations of the Stage 2 criterion scores, with SAW and TOPSIS recalculated under equal criterion weights to identify dominance-breaking and rank-reversal conditions. The oscillating water column–Savonius configuration, W1H3, remains first-ranked under all three sampled weight distributions because its normalized criterion scores are equal to or higher than those of every competing configuration across all five criteria. Criterion-wise sensitivity analysis shows that W1H3 is not outranked over the investigated weight range, although it ties with the point absorber–Savonius configuration, W2H3, when the full weight is assigned to mooring synergy or control compatibility. A crossover between W2H3 and the oscillating water column–hybrid Savonius–Darrieus configuration, W1H4, occurs at a co-location-feasibility weight of 0.384615. Across the three weight-sampling distributions, SAW and TOPSIS achieve complete-ranking agreement of 65.91–87.08%, with mean Spearman rank correlations of 0.9318–0.9742; the remaining differences are confined to the ordering of W2H3 and W1H4. Bounded score perturbations show that single one-point score change is sufficient to break the dominance of W1H3 over W2H3, whereas four changes are required for W2H3 to attain a unique first rank under both methods. The results demonstrate that W1H3 is rank-stable under the investigated weight and method variations for the adopted decision matrix, while the score-perturbation analysis identifies the bounded score changes under which the preferred ranking may change.

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1. Introduction

Marine renewable energy is increasingly recognized as an important component of future low-carbon energy systems, contributing to energy security, climate mitigation, and diversification of the global energy mix [1–5]. Among the marine resources, ocean waves and currents are characterized by high energy density and long-term availability. However, their standalone exploitation remains constrained by technical and economic challenges [1,2].

Hybrid wave–current energy systems have been proposed to improve energy utilization and reduce output variability by combining complementary marine resources within a common offshore infrastructure [3–5]. Depending on the degree of integration, the technologies may coexist within the same offshore environment, be co-located within a common lease or project footprint, or be co-constructed through shared support structures, mooring systems, electrical connections, or other physical interfaces [3,4]. Reviews by Ma et al. [6] and Song et al. [7] reported that increasing integration from co-location to co-construction introduces stronger requirements for structural compatibility, hydrodynamic interaction, layout, control, and mechanical response. These distinctions should be established at the early design stage, where concept selection strongly influences technical feasibility and subsequent system development.

Multi-criteria decision analysis (MCDA) methods are widely used to support concept selection decisions involving multiple and often conflicting technical, economic, and environmental criteria [8,9]. In renewable and marine energy applications, these methods have been applied to technology screening, site selection, and system comparison [8,10,11]. Among these methods, Simple Additive Weighting (SAW) is the most common method adopted due to its transparency and ease of implementation. Meanwhile, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is another method commonly used to rank alternatives according to their relative distances from ideal and negative-ideal solutions [8,9,12]. Studies by Taherdoost [12], Moreno-Rocha et al. [13], and Więckowski and Sałabun [14] have shown that ranking outcomes may vary with the MCDA formulation and criterion-weight assumptions, particularly when the evaluation criteria are qualitative, coupled, or partially interdependent. Consequently, examining a preferred hybrid concept under variations in criterion weights, MCDA formulations, and underlying criterion scores provides a more comprehensive assessment of ranking stability than relying on a single fixed-weight and fixed-score evaluation.

Ng and Ong [15] developed a two-stage MCDA procedure for the early-stage selection of floating hybrid wave–current energy concepts. In Stage 1, wave energy converter (WEC) and hydrokinetic turbine (HKT) technologies are screened separately based on evaluations from 11 experts. In Stage 2, the two highest-ranked WECs and two highest-ranked HKTs are combined to form four shortlisted hybrid configurations, which were subsequently evaluated using five integration criteria covering structural compatibility, PTO feasibility, mooring synergy, co-location feasibility, and control compatibility. The analysis identified the oscillating water column (OWC) WEC integrated with a Savonius vertical-axis HKT, denoted as W1H3, as the top-ranked configuration. In the adopted decision matrix, W1H3 attained the highest score for all five criteria and therefore componentwise dominated the competing configurations. This dominance implies that, under SAW, variations in non-negative criterion weights alone cannot cause another configuration to outrank

W1H3, although ties may occur under specific boundary-weighting conditions. However, the previous study did not establish whether the overall ranking remains stable under broader variations in criterion weighting, alternative MCDA formulations, or changes in the underlying criterion scores. These aspects therefore form the basis of the present ranking-stability analysis.

Accordingly, this study extends the baseline evaluation of Ng and Ong [15] through weight, method, and score sensitivity analyses applied to the four shortlisted WEC–HKT configurations. Weight sensitivity is examined through stochastic weight-space sampling and criterion-wise variation. The fixed normalized decision matrix is first evaluated using SAW across 10,000 weight scenarios generated from normalized-uniform random values, with additional Dirichlet distributions of $\alpha = 1$ and $\alpha = 0.5$ used to examine alternative weighting assumptions and greater representation of concentrated criterion-priority profiles. Criterion-wise sensitivity is then assessed by varying one criterion weight from 0 to 1 while proportionally redistributing the remaining weights. Method sensitivity is evaluated by applying TOPSIS to the same stochastic weight scenarios and comparing its rankings with those obtained from SAW using Spearman's rank correlation, complete-ranking agreement, top-rank agreement, and intermediate-pair agreement. Score sensitivity is subsequently examined through bounded one-point perturbations of the Stage 2 criterion scores to identify the conditions under which the componentwise dominance of W1H3 is broken or the baseline ranking is reversed. The analysis therefore evaluates the stability of the preferred ranking under variations in criterion weighting and MCDA formulation while also identifying the score changes under which that ranking may no longer be maintained.

2. Methodology

2.1. Baseline Hybrid Configurations and Normalized Decision Matrix

The hybrid configurations evaluated by Ng and Ong [15] are treated as the baseline concept-selection study for the present study. The same WEC notation is adopted, where W1 and W2 represent the oscillating water column (OWC) and point absorber (PA). Meanwhile, W3 and W4 represent overtopping and oscillating wave surge technologies. For the HKT components, H1 and H2 represent the Darrieus and Gorlov helical models, respectively, while H3 and H4 represent the Savonius and hybrid Savonius–Darrieus (Hybrid) turbines. Based on the Stage 1 screening, the two highest-ranked WECs, W1 and W2, and the two highest-ranked HKTs, H3 and H4, are combined to form four shortlisted hybrid configurations: W1H3 (OWC–Savonius), W1H4 (OWC–hybrid Savonius–Darrieus), W2H3 (PA–Savonius), and W2H4 (PA–hybrid Savonius–Darrieus). The present study therefore evaluates the ranking stability and consistency among these four shortlisted configurations rather than reassessing the Stage 1 technology-screening results.

The four shortlisted hybrid configurations are evaluated against five integration criteria: structural compatibility, power take-off (PTO) feasibility, mooring synergy, co-location feasibility, and control compatibility. These criteria represent distinct primary structural, mechanical, station-keeping, spatial, and operational aspects relevant to early-stage WEC–HKT integration. Interactions may occur among the criteria because the corresponding engineering subsystems are physically coupled. However, they are treated as separate dimensions in the MCDA calculations to maintain a consistent evaluation structure and minimize potential double counting.

The Stage 2 decision matrix comprises rubric-based ordinal engineering scores assigned on a five-point scale, ranging from very poor (1) to excellent (5), based on the engineering assessment reported by Ng and Ong [15]. The Stage 2 matrix represents a single rubric-based engineering assessment rather than separate assessor-level evaluations. Accordingly, these scores are not interpreted as means, medians, modes, rounded averages, or consensus values derived from the 11-expert Stage 1 survey, rather they are interpreted as a raw hybrid scoring matrix, as presented in Table 1.

Table 1. Scoring matrix for hybrid WEC–HKT configurations taken from Ng and Ong [15].

Criterion	W1H3	W1H4	W2H3	W2H4
C1—Structural Compatibility	4	3	3	2
C2—Power Take-Off (PTO) Feasibility	4	3	3	2
C3—Mooring Synergy	4	3	4	3
C4—Co-Location Feasibility	5	4	3	2
C5—Control Compatibility	4	3	4	3

All five evaluation criteria are benefit criteria; each raw score x_{ij} is transformed using linear maximum normalization. The corresponding normalized score is given as

$$n_{ij} = \frac{x_{ij}}{x_j^{max}} \tag{1}$$

where x_{ij} is the raw score of configuration i under criterion j, and ${x_j}^{max}$ is the maximum score observed for criterion j. The resulting dimensionless decision matrix, with values ranging from 0 to 1, is presented in Table 2. An equal-weight baseline vector, w_j = 0.20 for all five criteria, is adopted as the deterministic reference case.

Table 2. Baseline normalized decision matrix for the four shortlisted hybrid configurations.

Criterion	Weight	W1H3	W1H4	W2H3	W2H4
C1—Structural Compatibility	0.2	1	0.75	0.75	0.5
C2—Power Take-Off (PTO) Feasibility	0.2	1	0.75	0.75	0.5
C3—Mooring Synergy	0.2	1	0.75	1	0.75
C4—Co-Location Feasibility	0.2	1	0.8	0.6	0.4
C5—Control Compatibility	0.2	1	0.75	1	0.75

A configuration exhibits componentwise dominance when its normalized score is at least as high as that of every competing configuration for every criterion and strictly higher for at least one criterion [16]. W1H3 attains the maximum normalized score of 1.00 for all five criteria and therefore componentwise dominates the other three configurations. Consequently, under any non-negative normalized weight vector, its SAW score cannot be lower than those of the competing configurations, although boundary weighting cases may yield equal SAW scores among configurations.

The normalized matrix is treated as a fixed input throughout stochastic weight-variation and cross-method consistency analyses; only the separate bounded score-perturbation analysis modifies the original criterion scores. The effect of changing decision priorities is examined by varying the criterion weights across the sampled scenarios while keeping the normalized criterion scores unchanged. The core stochastic evaluation procedure, in which the same fixed normalized decision matrix and weight scenarios are applied to SAW and TOPSIS before ranking agreement is assessed, is summarized in Figure 1.

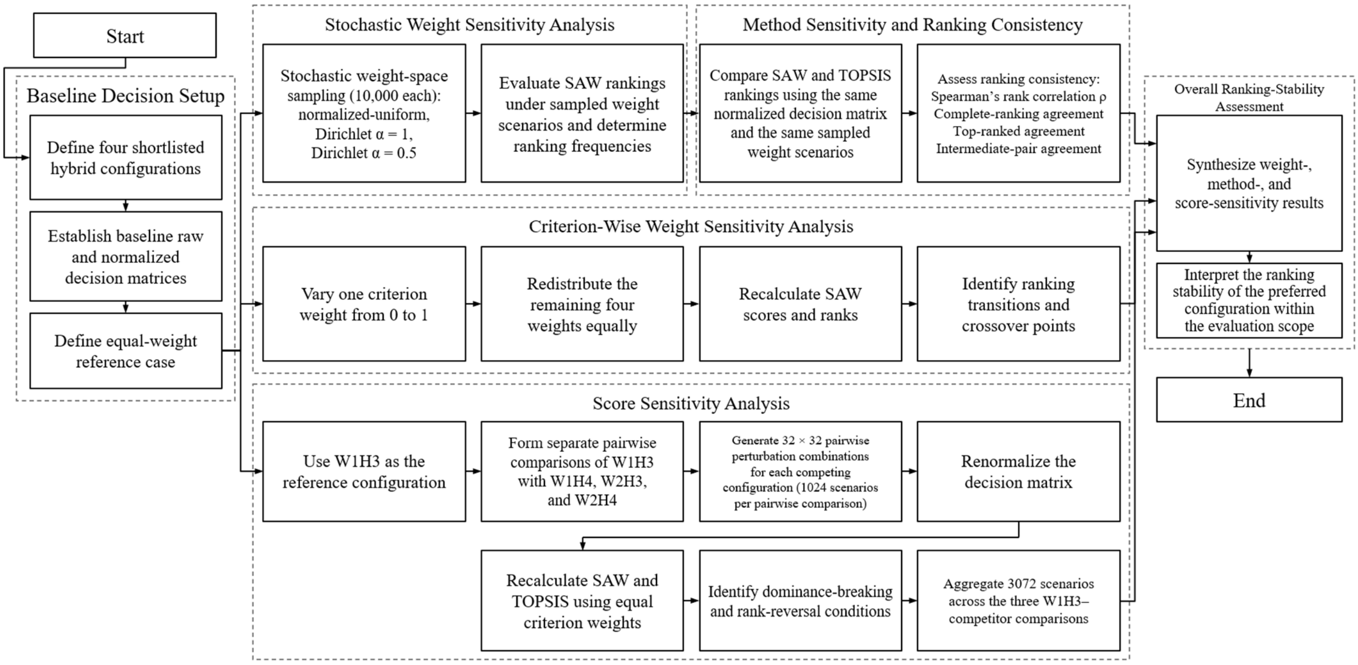

Figure 1. Overall methodology for the stochastic weight-space, criterion-wise sensitivity, cross-method consistency, and bounded score-perturbation analyses.

2.2. Stochastic Weight-Space Sampling

Stochastic weight-space sampling is performed following the Monte Carlo principle of repeated random sampling described by Rubinstein and Kroese [17]. A fixed random seed of 42 is used to initialize the stochastic sampling procedure in MATLAB, version R2026a to ensure reproducibility. For the primary normalized-uniform sampling case, $N = 10{,}000$ weight scenarios are generated. For each scenario s, five independent random values are generated such that $u_j^{(s)} \sim U(0,1)$. The criterion weights are obtained by dividing each random value by the sum of the five values within the same scenario, given as follows.

$$w_j^{(s)} = \frac{u_j^{(s)}}{\sum_{k=1}^{5} u_k^{(s)}},\ j = 1, \ldots, 5, \tag{2}$$

where $w_j^{(s)}$ is the normalized weight assigned to criterion j in scenario s. The resulting weight vectors are positive and satisfy $\sum_{j=1}^{5} w_j^{(s)} = 1$. This distribution is referred to as the normalized-uniform sampling case. Although the underlying random values $u_j^{(s)}$ are uniformly distributed, the resulting normalized weight vectors are not uniformly distributed over the simplex defined by five non-negative weights summing to one.

To assess if the ranking results are sensitive to the weight-generation assumption, two additional sets of 10,000 weight vectors are generated from symmetric Dirichlet distributions. The first distribution used the concentration vector $\alpha = (1, 1, 1, 1, 1)$, which provides uniform sampling over the simplex. The second set used $\alpha = (0.5, 0.5, 0.5, 0.5, 0.5)$, which places greater probability near the simplex boundaries and therefore provides greater representation of scenarios in which one or a small number of criteria receive relatively large weights. Larger symmetric concentration parameters, such as $\alpha = 2$ or $\alpha = 10$, were not considered in this study because they increasingly concentrate the sampled weights around the equal-weight region, whereas the purpose of the additional Dirichlet cases was to broaden the representation from uniform simplex coverage toward more concentrated criterion-priority profiles.

For each scenario s and criterion j, an intermediate positive random variable $g_j^{(s)}$ is generated before normalization. For the Dirichlet case with $\alpha = 1$, the variable is calculated as $g_j^{(s)} = -\ln\left(r_j^{(s)}\right)$, where $r_j^{(s)} \sim U(0,1)$ is an independent uniformly distributed random value generated. This transformation produces a Gamma-distributed variable with shape parameter $\alpha = 1$ and a unit scale.

For the Dirichlet case with $\alpha = 0.5$, the intermediate variable is calculated as $g_j^{(s)} = 0.5\left(z_j^{(s)}\right)^2$, where $z_j^{(s)} \sim N(0,1)$ is an independent standard normally distributed random value. This transformation produces a Gamma-distributed variable with shape parameter $\alpha = 0.5$ and a unit scale. For both Dirichlet cases, the final criterion weights are obtained using

$$w_j^{(s)} = \frac{g_j^{(s)}}{\sum_{k=1}^{5} g_k^{(s)}},\ j = 1, \ldots, 5. \quad (3)$$

where j denotes the criterion index, and s denotes the sampled scenario. Normalizing the five independent Gamma-distributed variables with a common scale parameter produces a Dirichlet-distributed weight vector. Normalization also ensures that all criterion weights are positive and sum to one within each scenario.

Each sampling case comprises 10,000 weight scenarios. The normalized decision matrix presented in Table 2 is held fixed, while only the criterion weights are varied. The three sampling cases therefore represent different sampled weighting assumptions rather than exhaustive coverage of all possible decision-priority profiles. The stochastic weight-space analysis is used to assess the sensitivity of the ranking to variations in criterion weighting. As the first-ranked position of W1H3 under SAW follows from its componentwise dominance in the fixed decision matrix, the resulting weight-induced variation is therefore expected primarily in the intermediate rankings. The same sampled weight scenarios are subsequently used to assess ranking consistency between SAW and TOPSIS. Uncertainty in the criterion scores is examined separately through bounded score-perturbation analysis.

2.3. Weight Sensitivity Analysis Using Simple Additive Weighting (SAW)

The Simple Additive Weighting (SAW) method is used to determine the ranking of the four hybrid configurations under each generated criterion-weight scenario. For scenario s, the SAW score of configuration i is calculated as the weighted sum of its normalized criterion scores [17]:

$$S_i^{(s)} = \sum_{j=1}^{5} w_j^{(s)} n_{ij}, \quad (4)$$

where $S_i^{(s)}$ is the SAW score of configuration i in scenario s, $w_j^{(s)}$ is the weight assigned to criterion j in that scenario, and n_{ij} is the fixed normalized score of configuration i under criterion j, as presented in Table 2.

The SAW scores are calculated for all four hybrid configurations using each of the 10,000 weight vectors generated for the normalized-uniform, Dirichlet $\alpha = 1$, and Dirichlet $\alpha = 0.5$ sampling cases described in Section 2.2. Within each scenario, the configurations are ranked in descending order of SAW score, with Rank 1 assigned to the highest-scoring configuration and Rank 4 assigned to the lowest-scoring configuration. The scenario-level rankings are subsequently aggregated to determine the frequency with which each configuration occupies each rank position under the three sampled weighting assumptions.

2.4. Criterion-Wise Sensitivity Analysis

A criterion-wise sensitivity analysis is conducted to examine the effect of changing the importance of each individual criterion on the SAW ranking. The analysis also identifies changes in the intermediate ranking order and the criterion-weight values at which ranking transitions occur.

For each sensitivity case, the weight of a selected criterion q is varied from 0 to 1 using 201 equally spaced values, corresponding to a weight increment of $\Delta w_q = 0.005$. The remaining four criterion weights are redistributed equally according to

$$w_j = \frac{1 - w_q}{4},\ j \neq q, \tag{5}$$

where w_q is the weight of the criterion being varied, and w_j is the weight assigned to each of the remaining criteria. This formulation ensures that all weights remain non-negative and that $\sum_{j=1}^{5} w_j = 1$ at every point in the sweep. The procedure is repeated separately for C1–C5 while the normalized decision matrix in Table 2 is held fixed. Note that the equal-weight reference case, $w_j = 0.20$, is included as a baseline marker in each criterion-wise sensitivity plot.

At each weight value, the SAW scores of the four hybrid configurations are recalculated using Equation (4), and the configurations are ranked in descending order of score. Scores differing by no more than 1×10^{-10} are treated as equal, and tied configurations are retained at the same rank rather than being separated according to their order in the dataset.

2.5. Method Sensitivity and Ranking Consistency

Method sensitivity and ranking consistency are assessed by comparing the SAW results with those obtained using the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). For each sampling case described in Section 2.2, both methods are applied to the same normalized decision matrix and identical sets of criterion-weight scenarios, ensuring that any differences in ranking arise from the MCDA formulation rather than from differences in the input data or weighting conditions. The resulting rankings are then compared to evaluate the consistency between the additive SAW approach and the distance-based TOPSIS approach.

The maximum-normalized decision matrix n_{ij} presented in Table 2 is used in TOPSIS, without applying an additional vector-normalization procedure. For each scenario s, the weighted normalized value is calculated as

$$v_{ij}^{(s)} = w_j^{(s)} n_{ij}, \tag{6}$$

where $v_{ij}^{(s)}$ is the weighted normalized value of configuration i under criterion j, $w_j^{(s)}$ is the weight of criterion j in scenario s, and n_{ij} is the normalized score presented in Table 2.

Since all five criteria are benefit criteria, the positive-ideal and negative-ideal solutions are defined, as reported by Moreno-Rocha et al. [13] and Mohamed et al. [18]:

$$A_j^{+(s)} = \left\{ \max\left(v_{ij}^{(s)}\right) \middle| \ j = 1, 2, \ldots, m \right\} \tag{7}$$

$$A_j^{-(s)} = \left\{ \min\left(v_{ij}^{(s)}\right) \middle| \ j = 1, 2, \ldots, m \right\} \tag{8}$$

where $A_j^{+(s)}$ and $A_j^{-(s)}$ are the positive-ideal and negative-ideal values, respectively, for criterion j in scenario s, $n = 4$ is the number of hybrid configurations, and $m = 5$ is the number of criteria.

The Euclidean distances of each configuration from the positive-ideal and negative-ideal solutions are then calculated as

$$D_i^{+(s)} = \sqrt{\sum_{j=1}^{m} \left(v_{ij}^{(s)} - A_j^{+(s)} \right)^2} \tag{9}$$

$$D_i^{-(s)} = \sqrt{\sum_{j=1}^{m} \left(v_{ij}^{(s)} - A_j^{-(s)} \right)^2} \tag{10}$$

where $D_i^{+(s)}$ and $D_i^{-(s)}$ denote the distances of configuration i from the positive-ideal and negative-ideal solutions. The relative closeness coefficient of configuration i is obtained as

$$CC_i^{(s)} = \frac{D_i^{-(s)}}{D_i^{+(s)} + D_i^{-(s)}} \tag{11}$$

A higher value of the closeness coefficient indicates that a configuration is relatively closer to the positive-ideal solution and farther from the negative-ideal solution. It is therefore preferred in the TOPSIS ranking. In this study, the four hybrid configurations are ranked in descending order of the closeness coefficient. Ranking orders are therefore obtained independently from SAW and TOPSIS using the same normalized matrix and weight-sampling cases described in Section 2.2.

The degree of agreement between SAW and TOPSIS is then quantified using Spearman's rank correlation coefficient and is expressed as [19]:

$$\rho^{(s)} = 1 - \frac{6\sum_{i=1}^{N_a} \left(d_i^{(s)} \right)^2}{N_a(N_a^2 - 1)} \tag{12}$$

where $d_i^{(s)}$ is the difference between the SAW and TOPSIS ranks of configuration i in scenario s, and $N_a = 4$ is the number of hybrid configurations. The coefficient ranges from -1 to 1, where $\rho = 1$ indicates identical ranking orders; values approaching 1 indicate increasingly strong ranking agreement, $\rho = 0$ indicates no monotonic association between the two rankings, and $\rho = -1$ indicates an exactly reversed ranking order. A higher $\rho^{(s)}$ value therefore represents greater consistency between the rankings obtained using SAW and TOPSIS.

Ranking consistency between SAW and TOPSIS is evaluated using three agreement measures together with Spearman's rank correlation coefficient. Complete-ranking agreement is recorded when both methods assign identical ranks to all four configurations, while top-ranked agreement is recorded when both methods identify the same first-ranked configuration. Intermediate-pair agreement is recorded when SAW and TOPSIS assign the same relative ordering to W2H3 and W1H4. Spearman's rank correlation is additionally used to quantify the degree of association between the complete ranking orders.

2.6. Bounded Score-Perturbation Analysis

Subsequently, a bounded score-perturbation analysis is conducted using both SAW and TOPSIS to examine the conditions under which the componentwise dominance of W1H3 is broken or the baseline ranking is reversed. The original five-point scoring matrix presented in Table 1 is used. For each analysis, the criterion scores of W1H3 are either retained or reduced by one point, while the scores of one competing configuration are either retained or increased by one point. The remaining two configurations are kept at their original scores. All perturbed scores remain within the original range from 1 to 5.

With five criteria and two possible states for each score, 32 perturbation patterns are generated for W1H3 and 32 for the selected competing configuration. Combining these patterns produces 32 × 32 = 1024 scenarios for each pairwise comparison. The procedure is performed separately for W1H4, W2H3, and W2H4, giving 3072 perturbation scenarios in total.

For each scenario, the complete scoring matrix is renormalized using Equation (1), after which SAW and TOPSIS are recalculated using equal criterion weights of 0.20. Equal weights are retained to isolate the effect of score perturbation from that of weight variation. Scores differing by no more than 1×10^{-10} are treated as equal, with tied configurations assigned the same rank.

The analysis first determines the minimum number of score changes required to break the componentwise dominance of W1H3. It then determines the minimum number required for each competing configuration to tie or overtake W1H3, attain the first rank, and attain a unique first rank. Because breaking componentwise dominance does not necessarily produce a rank reversal, the two conditions are evaluated separately.

The present study is limited to the available Stage 2 assessment, which is represented by a single rubric-based engineering scoring matrix rather than separate assessor-level evaluations. Consequently, inter-assessor variability cannot be quantified, and the bounded score-perturbation analysis is interpreted as a deterministic assessment of ranking sensitivity rather than a probabilistic representation of expert-score uncertainty.

3. Results and Discussion

3.1. Stochastic Weight-Space Sample Coverage

The stochastic weight-space sample generated using the normalized-uniform procedure is illustrated in Figure 2. A total of 10,000 normalized weighting vectors are generated across the five integration criteria, of which 300 representative vectors are shown for visualization. The x-axis represents the five integration criteria, C1–C5, while the y-axis represents the dimensionless weight assigned to each criterion. The horizontal line at 0.20 represents the equal-weight reference case.

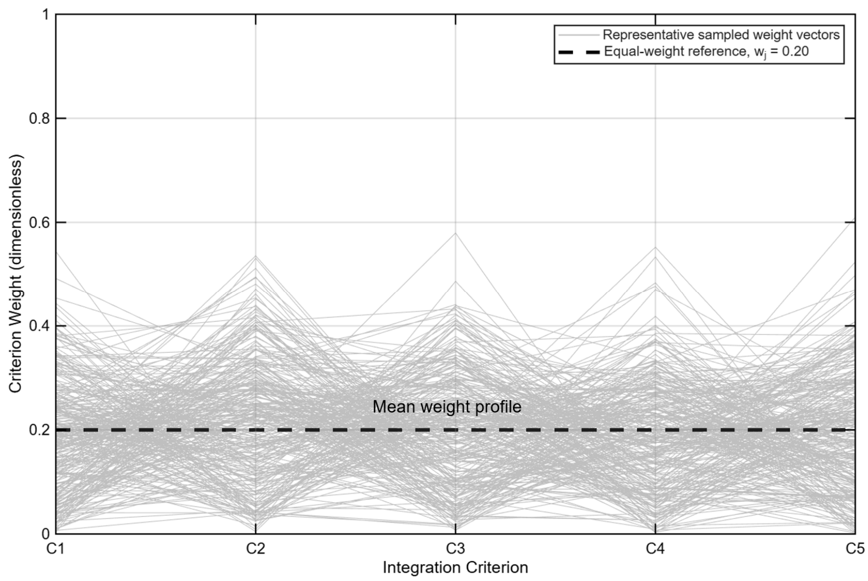

Figure 2. Representative normalized-uniform criterion-weight vectors selected from 10,000 generated scenarios.

The normalized-uniform sample is concentrated primarily away from the extreme regions of the feasible weight space. Only 0.81% of the generated scenarios contain a maximum criterion weight of at least 0.60, while no scenario contains a maximum weight of at least 0.80. Figure 2 therefore illustrates the sampled weight space rather than the full feasible weight space, with relatively limited representation of highly concentrated criterion-priority profiles.

To examine the influence of the sampling distribution on weight-space coverage, the normalized-uniform sample is compared with samples generated using Dirichlet $\alpha = 1$ and Dirichlet $\alpha = 0.5$ distributions, as summarized in Table 3. The percentage of scenarios containing a highest criterion weight of at least 0.60 increases from 0.81% for the normalized-uniform distribution to 13.00% for Dirichlet $\alpha = 1$ and 35.16% for Dirichlet $\alpha = 0.5$. For the more extreme threshold of 0.80, the corresponding percentages are 0.00%, 0.71%, and 8.00%, respectively.

Table 3. Weight-space sample coverage under the three weight-sampling distributions.

Weight-Sampling Distribution	Maximum Weight $\geq$ 0.60 (%)	Maximum Weight $\geq$ 0.80 (%)
Normalized uniform	0.81	0.00
Dirichlet $\alpha = 1$	13.00	0.71
Dirichlet $\alpha = 0.5$	35.16	8.00

The results demonstrate that the three sampling distributions provide progressively greater representation of concentrated criterion-priority profiles. Among the cases examined, Dirichlet $\alpha = 0.5$ provides the greatest coverage of high-weight regions, whereas the normalized-uniform procedure predominantly represents more moderate weighting conditions. The use of the three distributions therefore broadens the range of weighting conditions considered in the subsequent ranking-sensitivity analysis.

3.2. Stochastic Weight Sensitivity of SAW Rankings

The effect of stochastic criterion-weight variations on the SAW ranking is assessed using the normalized-uniform, Dirichlet $\alpha = 1$, and Dirichlet $\alpha = 0.5$ samples described in Section 3.1. Across all three sampling distributions, W1H3 remains the first-ranked configuration, and W2H4 remains fourth, indicating that variation in criterion weighting does not alter the highest- and lowest-ranked configurations for the fixed decision matrix. Under the normalized-uniform sampling case, W1H3 is ranked first in 100% of the 10,000 scenarios, while W2H4 is ranked fourth in 100% of the scenarios.

Weight variation primarily affects the relative ordering of W2H3 and W1H4. As summarized in Table 4, W2H3 is ranked second in 89.29% of the normalized-uniform scenarios, decreasing to 80.30% under Dirichlet $\alpha = 1$ and 74.55% under Dirichlet $\alpha = 0.5$. Conversely, the second-rank frequency of W1H4 increases from 10.71% to 19.70% and 25.45%, respectively.

Table 4. SAW ranking results under the three stochastic weight-sampling distributions.

Weight-Sampling Distribution	W1H3 Rank 1 (%)	W2H3 Rank 2 (%)	W1H4 Rank 2 (%)	W2H4 Rank 4 (%)
Normalized uniform	100.00	89.29	10.71	100.00
Dirichlet $\alpha = 1$	100.00	80.30	19.70	100.00
Dirichlet $\alpha = 0.5$	100.00	74.55	25.45	100.00

The complete ranking-frequency distribution for the normalized-uniform case is illustrated in Figure 3. Across the 10,000 sampled weight scenarios, W1H3 occupies Rank 1 in all cases, while W2H4 occupies Rank 4 throughout. W2H3 is ranked second in 89.29% of the scenarios and third in 10.71%, whereas W1H4 exhibits a complementary distribution, occupying Rank 2 in 10.71% and Rank 3 in 89.29% of the scenarios.

The persistent first-ranked position of W1H3 follows from the structure of the fixed normalized decision matrix, in which W1H3 attains the maximum normalized score for all five criteria and exceeds each competitor in at least one criterion. Consequently, under positive normalized criterion weights, its SAW score cannot be lower than those of the competing configurations. The stochastic analysis therefore confirms the expected first-ranked position of W1H3 across the sampled weight scenarios while evaluating the sensitivity of the remaining ranking order to variations in criterion priorities.

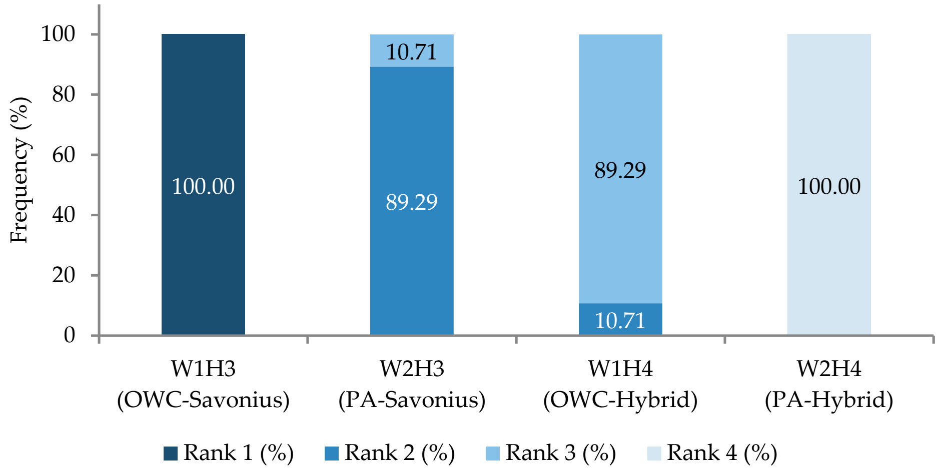

Figure 3. SAW ranking-frequency distribution of the four hybrid configurations across 10,000 normalized-uniform weight scenarios.

The underlying ranking also reflects the Stage 2 scoring matrix adopted from the baseline concept-selection study by Ng & Ong [15], in which W1H3 received the highest criterion score across the five integration criteria. These scores are treated as the fixed engineering basis of the present weight-sensitivity analysis, while uncertainty in the scores themselves is examined separately through the bounded score-perturbation analysis.

In short, increasing the representation of concentrated criterion-priority profiles changes the frequency with which W2H3 and W1H4 occupy the second and third positions but does not alter the first-ranked position of W1H3 or the fourth-ranked position of W2H4. For the adopted decision matrix, stochastic weight variation therefore affects the intermediate ranking order rather than the preferred configuration.

3.3. Criterion-Wise Weight Sensitivity Analysis

The criterion-wise sensitivity results are presented in Figures 4–8. For each analysis, the weight of one integration criterion is varied from 0 to 1, while the remaining total weight is distributed equally among the other four criteria. The corresponding SAW scores and rankings of the four hybrid configurations are evaluated across the full weight range.

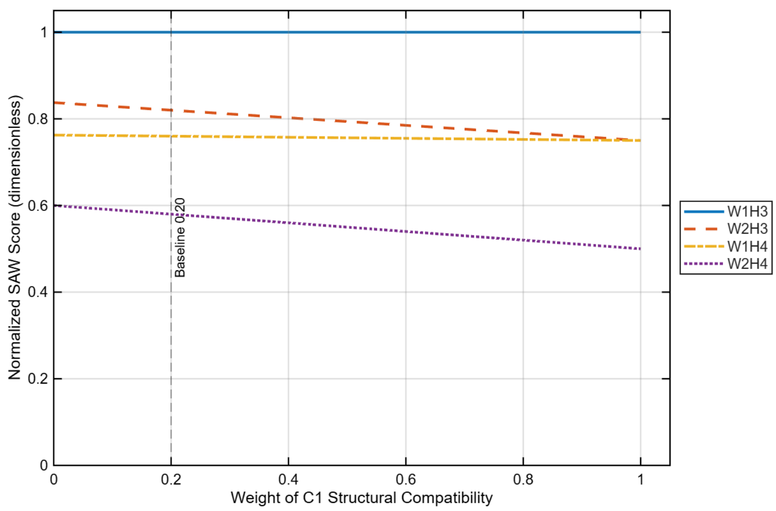

Figure 4. Sensitivity of the normalized SAW scores to the weight assigned to C1 structural compatibility.

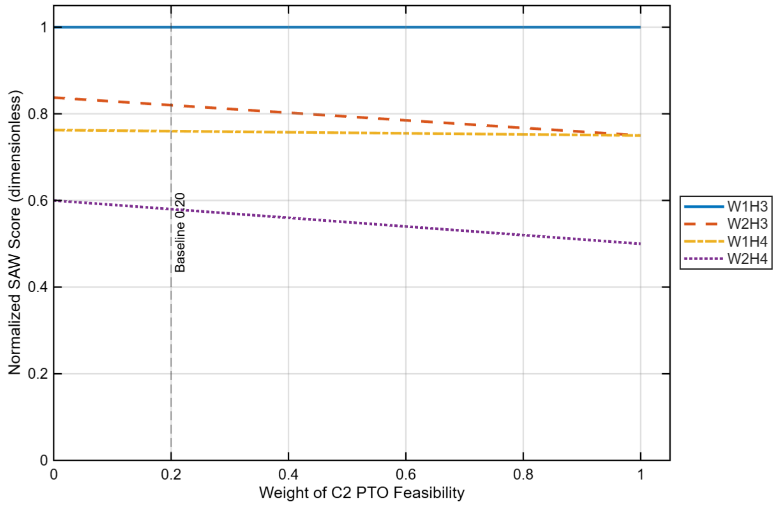

Figure 5. Sensitivity of the normalized SAW scores to the weight assigned to C2 PTO feasibility.

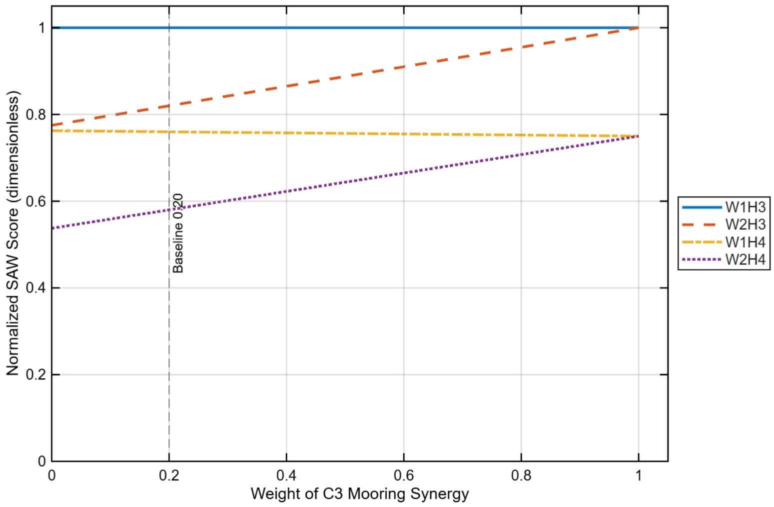

Figure 6. Sensitivity of the normalized SAW scores to the weight assigned to C3 mooring synergy.

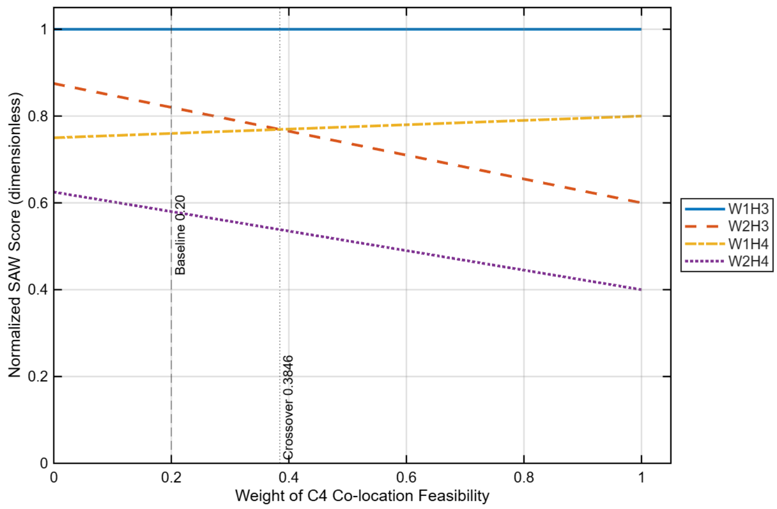

Figure 7. Sensitivity of the normalized SAW scores to the weight assigned to C4 co-location feasibility.

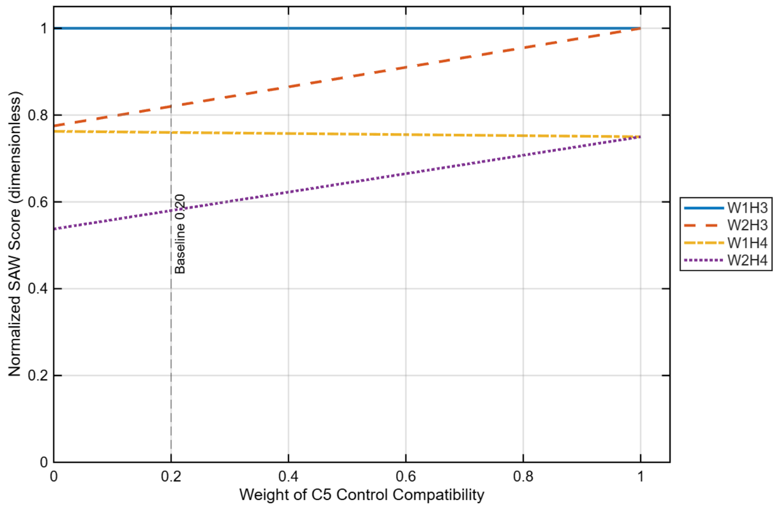

Figure 8. Sensitivity of the normalized SAW scores to the weight assigned to control compatibility.

Figure 4 shows the sensitivity of the SAW scores to changes in the weight assigned to C1 structural compatibility. W1H3 remains the highest-ranked configuration and W2H4 remains the lowest-ranked configuration over the full range of w_{C1}. W2H3 ranks above W1H4 for $0 \leq w_{C1} < 1$, with the score difference progressively decreasing as the weight assigned to C1 increases. At $w_{C1} = 1$, W2H3 and W1H4 have identical SAW scores because both configurations have the same normalized C1 score of 0.75.

Figure 5 shows a similar response for C2 PTO feasibility. W1H3 retains the highest score across the full range, followed by W2H3 and W1H4. W2H4 remains the lowest-scoring configuration. Since W2H3 and W1H4 have the same normalized score for C2, varying this criterion does not cause a change in their ranking order.

The sensitivity results for C3 mooring synergy are shown in Figure 6. As the weight of C3 increases, W2H3 benefits from its maximum normalized score of 1.00 and approaches W1H3. At a C3 weight of 1, W1H3 and W2H3 obtain the same SAW score and are tied for first position. At the same endpoint, W1H4 and W2H4 also obtain the same score because both configurations have a normalized C3 score of 0.75. No configuration overtakes W1H3 within the tested range.

Figure 7 presents the results for C4 co-location feasibility. A ranking crossover is observed between W2H3 and W1H4. W2H3 remains above W1H4 when the C4 weight is below 0.384615. The two configurations obtain the same SAW score at a C4 weight of 0.384615. When the C4 weight exceeds this value, W1H4 moves above W2H3. This occurs because W1H4 has a higher normalized score for co-location feasibility, while W2H3 has higher scores for mooring synergy and control compatibility.

The sensitivity results for C5 control compatibility are shown in Figure 8. The trend is similar to that observed for C3. W2H3 approaches W1H3 as the C5 weight increases because both configurations have the maximum normalized score for this criterion. At a C5 weight of 1, W1H3 and W2H3 are tied for first position, while W1H4 and W2H4 are tied at a lower score.

Overall, W1H3 remains either uniquely first-ranked or tied for first across the full criterion-wise weight range and is not outranked by any competing configuration. Endpoint ties with W2H3 occur when either C3 or C5 receives the entire criterion weight. The only interior ranking crossover occurs between W2H3 and W1H4 under variations of C4, at $w_{C4} = 0.384615$. These results indicate that criterion-wise weight variation primarily affects the ordering of the intermediate configurations rather than the preferred configuration for the fixed decision matrix.

3.4. Method Sensitivity and Ranking Consistency Results

Method sensitivity is assessed by comparing the rankings obtained using SAW and TOPSIS under the same sampled criterion-weight scenarios. The TOPSIS ranking frequency distribution is presented in Table 5. Across the 10,000 stochastic weight scenarios, W1H3 is still ranked first in 100.00% of cases, while W2H4 is also ranked fourth in 100.00% of cases. W2H3 is ranked second in 55.20% of cases and third in 44.80% of cases. W1H4 is ranked second in 44.80% of cases and third in 55.20% of cases. The TOPSIS results remain the same as the highest-ranked and lowest-ranked configurations observed in the SAW results, while variation is restricted to the second and third positions.

Table 5. Ranking frequency distribution of the four hybrid configurations across 10,000 stochastic weight scenarios using TOPSIS.

Hybrid Configuration	Rank 1 (%)	Rank 2 (%)	Rank 3 (%)	Rank 4 (%)
W1H3 (OWC–Savonius)	100.00	0.00	0.00	0.00
W2H3 (PA–Savonius)	0.00	55.20	44.80	0.00
W1H4 (OWC–Hybrid Savonius–Darrieus)	0.00	44.80	55.20	0.00
W2H4 (PA–Hybrid Savonius–Darrieus)	0.00	0.00	0.00	100.00

Compared with SAW, TOPSIS produces a different distribution of the intermediate rankings. Under SAW, W2H3 is ranked second in 89.29% of the normalized-uniform scenarios, compared with 55.20% under TOPSIS. This difference arises from the distinct aggregation logic of the two methods. SAW ranks the configurations by weighted additive scores, while TOPSIS ranks them according to their relative distances from the ideal and negative-ideal solutions.

The difference is associated with the criterion profiles of W2H3 and W1H4. W2H3 has higher normalized scores for C3 mooring synergy and C5 control compatibility, whereas W1H4 has a higher score for C4 co-location feasibility. Both configurations have equal scores for C1 structural compatibility and C2 PTO feasibility. Consequently, the two MCDA formulations differ mainly in their treatment of these intermediate trade-offs, while the first- and fourth-ranked configurations remain unchanged.

Ranking consistency across the three weight-sampling distributions is summarized in Table 6 and Figure 9. Complete-ranking agreement between SAW and TOPSIS increases from 65.91% under normalized-uniform sampling to 80.07% under Dirichlet $\alpha = 1$ and 87.08% under Dirichlet $\alpha = 0.5$. The corresponding mean Spearman rank correlations increase from 0.9318 to 0.9601 and 0.9742, respectively.

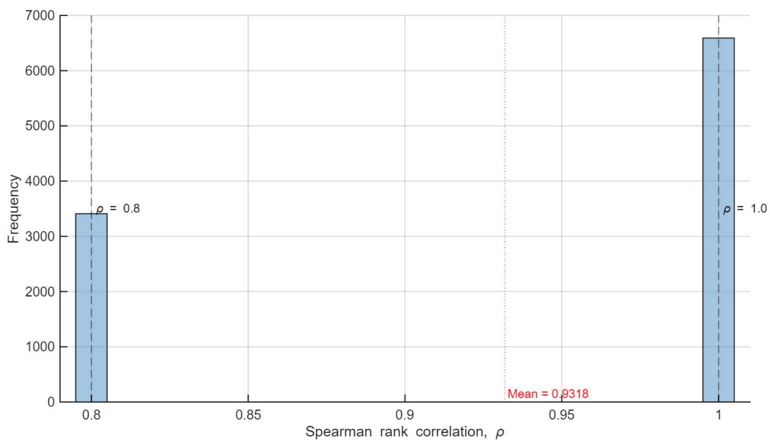

Figure 9. Distribution of Spearman's rank correlation between SAW and TOPSIS across all stochastic weight scenarios.

Table 6. Ranking consistency between SAW and TOPSIS under the three weight-sampling distributions.

Weight-Sampling Distribution	Complete-Ranking Agreement (%)	Mean Spearman's (ρ)
Normalized uniform	65.91	0.9318
Dirichlet $\alpha = 1$	80.07	0.9601
Dirichlet $\alpha = 0.5$	87.08	0.9742

For the normalized-uniform case, complete-ranking agreement between SAW and TOPSIS occurs in 65.91% of the 10,000 scenarios. The remaining 34.09% differ only through an exchange of W2H3 and W1H4; hence, the intermediate-pair agreement is also 65.91%. Both methods identify W1H3 as the first-ranked configuration in all scenarios, giving a top-rank agreement of 100%. The Spearman rank correlation takes values of either 1.0, when the complete rankings are identical, or 0.8, when W2H3 and W1H4 exchange positions. This produces the bimodal distribution shown in Figure 9. The mean value of $\rho = 0.9318$ therefore represents the average rank correlation.

Overall, SAW and TOPSIS are consistent in identifying W1H3 as the preferred configuration and W2H4 as the lowest-ranked configuration across the investigated weight scenarios. Method sensitivity is confined to the ordering of W2H3 and W1H4, indicating that the intermediate ranking is more sensitive to the choice of MCDA formulation than the preferred configuration.

3.5. Bounded Score-Perturbation Analysis Results

The bounded score-perturbation results are summarized in Table 7. Among the three competing configurations, W2H3 requires the fewest score changes to challenge the baseline ranking. A single one-point score change is sufficient to break the componentwise dominance of W1H3 over W2H3, whereas four changes are required for W2H3 to attain a unique first rank under both SAW and TOPSIS.

Table 7. Minimum number of one-point criterion-score changes required to alter the baseline dominance and ranking outcomes.

Competing Configuration	Dominance-Breaking Changes	Changes to Attain First Rank Under Both Methods	Changes to Attain Unique First Rank Under Both Methods	Ranking Outcome
W1H4	2	5	5	Unique first rank attained
W2H3	1	4	4	Unique first rank attained
W2H4	2	9	Not attained	Shared first rank attained

A representative four-change case is obtained by reducing the C1 score of W1H3 from 4 to 3 and increasing the C1, C2, and C4 scores of W2H3 from 3 to 4. The resulting score profiles are [3–5] for W1H3 and [4] for W2H3. Following renormalization, the corresponding SAW scores are 0.95 and 0.96, respectively. The TOPSIS closeness coefficients are 0.7813 and 0.8158 for W1H3 and W2H3, respectively. W2H3 therefore becomes the unique first-ranked configuration under both methods.

For W1H4, two score changes are required to break the dominance of W1H3, while five changes are required for W1H4 to attain a unique first rank under both methods. For W2H4, two changes are sufficient to break the dominance relationship. However, nine changes are required for W2H4 to attain a shared first rank. No perturbation scenario within the defined score variations allows W2H4 to attain a unique first rank.

The results demonstrated that breaking componentwise dominance does not necessarily result in a change in the first-ranked configuration. W2H3 is the closest competitor to

W1H3 because it has the same baseline scores as W1H3 for C3 mooring synergy and C5 control compatibility, while differing from W1H3 by only one score level for C1 structural compatibility, C2 PTO feasibility, and C4 co-location feasibility. Consequently, fewer score changes are required for W2H3 than for W1H4 or W2H4 to attain the first rank.

The present study is limited to the available Stage 2 assessment, which is represented by a single rubric-based engineering scoring matrix rather than separate assessor-level evaluations. The bounded perturbation results should therefore be interpreted as deterministic ranking-sensitivity thresholds, rather than as probabilities of score variation or estimates of inter-assessor uncertainty. The analysis identifies how far the adopted Stage 2 scores must change before the baseline dominance relationship or preferred ranking is altered.

The computational demand of the present stochastic ranking analysis is modest because each weight scenario is evaluated independently using matrix-based SAW and TOPSIS calculations. For larger decision matrices or greater numbers of stochastic scenarios, the calculations can be processed in batches or parallelized because the individual scenarios are independent.

4. Conclusions

A stochastic sensitivity and consistency analysis is conducted for the concept selection of hybrid wave–current energy systems using four shortlisted configurations and five integration criteria. The analysis evaluates ranking sensitivity to criterion weighting using stochastic weight-space sampling and criterion-wise variation; method sensitivity through comparisons of SAW and TOPSIS; and score sensitivity through bounded perturbations of the Stage 2 criterion scores.

The results show that W1H3 remains first-ranked under the normalized-uniform, Dirichlet $\alpha = 1$, and Dirichlet $\alpha = 0.5$ weight-sampling distributions. W1H3 remains first-ranked under all three weight-sampling distributions because its normalized criterion scores are equal to or higher than those of every competing configuration across all five criteria. Under criterion-wise weight variation, W1H3 is not outranked over the investigated range, although it shares the first position with W2H3 when the full weight is assigned to C3 mooring synergy or C5 control compatibility. The only interior ranking crossover occurs between W2H3 and W1H4 at a C4 co-location-feasibility weight of 0.384615.

The cross-method analysis shows that SAW and TOPSIS consistently identify W1H3 as the first-ranked configuration and W2H4 as the fourth-ranked configuration across the investigated weight scenarios, while methodological differences are confined to the ordering of W2H3 and W1H4. Complete-ranking agreement increases from 65.91% under normalized-uniform sampling to 80.07% under Dirichlet $\alpha = 1$ and 87.08% under Dirichlet $\alpha = 0.5$, with corresponding mean Spearman rank correlations of 0.9318, 0.9601, and 0.9742. For the normalized-uniform case, the remaining 34.09% of scenarios differ only through an exchange of W2H3 and W1H4.

The bounded score-perturbation analysis shows that breaking the componentwise dominance of W1H3 does not necessarily alter the preferred ranking. W2H3 is the closest competing configuration: A single one-point score change is sufficient to break the dominance relationship, whereas four changes are required for W2H3 to attain a unique first rank under both SAW and TOPSIS. The combined results therefore show that W1H3 is rank-stable under the investigated weight and method variations for the adopted decision matrix, while the score-perturbation analysis identifies the bounded score changes under which the preferred ranking can change.

The findings are limited to the four shortlisted configurations, five integration criteria, and the available Stage 2 assessment reported by Ng and Ong [15]. The Stage 2 assessment is represented by a single rubric-based engineering scoring matrix rather than separate assessor-level evaluations; therefore, inter-assessor variability cannot be quantified, and the bounded score perturbations should be interpreted as deterministic ranking-sensitivity tests rather than probabilistic representations of expert-score uncertainty. The findings support early-stage concept selection but do not demonstrate superior structural performance, energy efficiency, economic performance, or engineering reliability. Future evaluation of W1H3 should therefore incorporate site-specific numerical and engineering analyses considering water depth, bathymetry, directional wave conditions, current and tidal profiles, seabed properties, platform mass and inertia, mooring characteristics, OWC chamber and PTO parameters, Savonius turbine performance, and representative operational and extreme environmental conditions.

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Abbreviations

The following abbreviations are used in this manuscript:

HKT	Hydrokinetic Turbine
MCDA	Multi-Criteria Decision Analysis
OWC	Oscillating Water Column
PA	Point Absorber
PTO	Power Take-Off
WEC	Wave Energy Converter
W1H3	OWC–Savonius Configuration
W1H4	OWC–Hybrid Savonius–Darrieus Configuration
W2H3	PA–Savonius Configuration
W2H4	PA–Hybrid Savonius–Darrieus Configuration

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