Development Of Multicriteria Decision Analysis Framework for Optimisation of Renewable Energy Planning in Anambra State

OKAFOR, BETHRAND UZOMA[1], NWOBI-OKOYE, C.C[2]

[1] Department of Mechanical Engineering, Chukwuemeka Odumegwu Ojukwu University, Uli, Nigeria

Abstract- *The global energy sector is undergoing a significant transformation due to the urgent need to address climate change, ensure energy security and promote sustainable development. In Nigeria, particularly in Anambra State, persistent energy crises characterised by unreliable grid access, high dependence on fossil fuels and underutilised renewable energy (RE) resources emphasise the necessity for systematic energy planning. This study develops a Multi-Criteria Decision Analysis (MCDA) framework to optimise renewable energy planning in Anambra State, integrating technical, economic, environmental and social criteria. The research employs the Analytic Hierarchy Process (AHP) to prioritise decision criteria and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to rank renewable energy alternatives, including solar photovoltaic (PV), biomass, small-scale hydropower and wind energy. Primary data was collected through structured questionnaires administered to 20 stakeholders, including policymakers, energy experts and community leaders. The AHP results highlighted technical feasibility (0.22) and cost-effectiveness (0.18) as the most critical criteria, while environmental sustainability and energy equity received lower weights, reflecting pragmatic priorities. TOPSIS analysis ranked solar PV as the most viable alternative, aligning with Anambra's high solar irradiance, followed by hydropower, biomass and wind energy. The study emphasises the importance of stakeholder engagement, data availability and hybrid MCDA frameworks in energy planning. Recommendations include strengthening participatory mechanisms, enhancing technical capacity and aligning policies with Nigeria's Sustainable Development Goal (SDG) 7 targets. This research contributes to the discourse on sustainable energy transitions by providing a replicable, evidence-based framework for decision-making in resource-constrained settings. The findings advocate for a balanced approach to energy planning, ensuring reliability, affordability and long-term sustainability in Anambra State and similar regions.*

I. INTRODUCTION

Nigeria, the most populous nation in Africa, faces a significant energy crisis marked by chronic power shortages and a heavy reliance on fossil fuels, with only 53% of its population connected to the national grid and low per capita electricity consumption (144 kWh) (Jack & Jack, 2022). Despite its abundant renewable energy resources, such as solar and biomass, the country struggles to effectively harness these potentials (Vincent-Akpu, 2012). Anambra State exemplifies these challenges, with a rapidly growing population and increasing energy demand outpacing supply, forcing reliance on costly diesel generators (Ikejemba & Schuur, 2016). Transmission losses of over 30–35% exacerbate the inefficiencies (Ezenekwe et al., 2014). The state has substantial renewable energy potential, particularly solar and biomass, yet the effects of energy deficits are severe, leading to high operational costs for industries and unsustainable practices in rural communities (Al-Amin, 2014). While the Anambra State government aims to decentralize energy production and promote renewables, progress is hindered by fragmented planning and a lack of stakeholder engagement, underscoring the need for a comprehensive energy planning approach that integrates various priorities.

II. CONCEPTUAL REVIEW

Overview of Multi-Criteria Decision Analysis (MCDA) Methods

Multi-Criteria Decision Analysis (MCDA) methods help tackle decision-making issues involving multiple, often conflicting criteria, such as capital costs, carbon emissions, and job creation in energy planning (Woo, 2008; Shrestha & Acharya, 2015). The Analytic Hierarchy Process (AHP), a widely-

used MCDA technique (Saat, 2000), employs pairwise comparisons to assign weights and rank alternatives, making it effective for incorporating stakeholder input (Ramík, 2017; Deverka et al., 2012). Despite its advantages, AHP's dependence on subjective judgments introduces potential bias, and its computational complexity can grow in data-scarce environments, complicating its application (Montibeller & von Winterfeldt, 2015).

TOPSIS, developed by Parida (2019), is a straightforward method for ranking alternatives based on their geometric distance from an ideal solution. It identifies the option closest to the best outcome and furthest from the worst, making it effective for energy planning with quantifiable data (Al-Kurdi et al., 2019). In Anambra, TOPSIS could rank options like solar mini-grids and small hydropower (Barrera-Zapata et al., 2023), utilizing data from Nigeria's Rural Electrification Agency (Oladigbolu et al., 2020). However, TOPSIS assumes linear relationships among criteria, which can oversimplify complex energy planning considerations, such as environmental impacts and social acceptance, highlighting the need for careful criterion selection to obtain meaningful outcomes (T. Kaya & Kahraman, 2011; Ellis & Ferraro, 2017; Porzsolt et al., 2019).

PROMETHEE, developed by Brans and Vincke (1985) provides another robust MCDA approach, emphasising outranking relationships to compare alternatives. Unlike AHP's pairwise comparisons or TOPSIS's geometric distances, PROMETHEE uses preference functions to model decision-maker priorities, offering flexibility in handling qualitative and quantitative criteria (Deshmukh, 2013). However, PROMETHEE's complexity in defining preference functions can pose challenges in resource-constrained settings, where technical expertise may be limited (Podvezko & Podviezko, 2010). This underscores the need for capacity building to ensure effective implementation in Anambra (Roumell et al., 2020).

Criteria for Energy Planning

The selection of appropriate criteria forms the backbone of effective energy planning, particularly in developing regions where competing priorities demand careful balancing (Algarin et al., 2018).

These criteria must capture the multidimensional nature of energy systems, accounting not only for technical feasibility but also for environmental sustainability, economic viability and social equity (Frangopoulos & Keramioti, 2010). The environmental dimension encompasses factors such as solar irradiance, land use constraints and emissions profiles (Dupont et al., 2020), which collectively determine the ecological footprint of energy projects (Janković et al., 2019). Economic criteria play an equally pivotal role in energy planning (Algarín et al., 2017), with levelized cost of energy (LCOE) emerging as a crucial metric for comparing technologies across their lifecycle (Kabeyi & Olanrewaju, 2023). The social dimension of energy planning introduces complex, often overlooked considerations that can determine the success or failure of projects (Miller et al., 2013). Community acceptance has emerged as a make-or-break factor, particularly for technologies like waste-to-energy (WTE) plants that may face cultural resistance or NIMBY ("not in my backyard") opposition (Liu et al., 2018, Hou et al., 2019). Health impacts represent another crucial social criterion, as energy choices directly affect air quality and disease burdens (Ezzati et al., 2004). In a recent application of the Analytical Hierarchy Process (AHP) to energy planning in Southeast Nigeria (Oluchukwu & Emmanuel, 2019), environmental criteria received a 40% aggregate weighting, followed by economic (35%) and social (25%) factors, reflecting regional emphasis on ecosystem preservation amid rapid industrialisation (Patnaik, 2018; Ruzieva & Ruziev, 2024).

Technological advancements are reshaping these planning criteria in profound ways (Pinto, 2013). These innovations allow for more dynamic, evidence-based decision-making (Clemmons-Brown, 2023), though they also raise new challenges around data governance and digital divides in developing regions (Ciuriak, 2018). The political economy of energy planning further complicates criterion prioritisation (Martinez et al., 2011). Subsidy regimes, import dependencies and elite capture of energy rents often distort decision-making toward suboptimal outcomes (Clements et al., 2014). Nigeria's longstanding fuel subsidies, which consumed 4.5% of GDP in 2022, have artificially prolonged the competitiveness of gasoline generators against solar alternatives

(Heinemann et al., 2022), creating path dependencies that are difficult to break (Stache & Sydow, 2023). Similarly, the concentration of grid connections in urban areas reflects political calculations as much as economic ones (Acuto & Rayner, 2016), with rural communities frequently marginalized in resource allocation (Asthana et al., 2003).

III. METHODOLOGY

This study adopts a quantitative research approach to develop a MCDA framework aimed at optimising renewable energy planning in Anambra State, Nigeria. The methodology integrates the Analytic Hierarchy Process (AHP) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to evaluate and rank alternatives effectively. AHP determines the weights of decision criteria through pairwise comparisons, reflecting stakeholder preferences (Maroto et al., 2012; Poveda & Lipsett, 2013), while TOPSIS ranks alternatives based on their proximity to an ideal solution (Madanchian & Taherdoost, 2023). This hybrid approach, successfully applied in prior studies, balances subjective inputs with objective performance metrics, enhancing decision robustness (Chang et al., 2012; Kumar et al., 2020). However, AHP's reliance on subjective judgments may introduce bias, necessitating rigorous consistency checks. Primary data is collected through structured questionnaires administered to key stakeholders and experts in renewable energy planning. These questionnaires are meticulously designed to capture pairwise comparisons for AHP and performance ratings for TOPSIS, ensuring data suitability for both methods. Purposive sampling targets respondents with relevant expertise, bolstering the study's validity. While this approach offers timely and context-specific insights, its cross-sectional design may overlook temporal shifts in preferences, a limitation offset by the focus on expert input. Collectively, this methodology provides a structured, evidence-based framework for renewable energy decision-making, though its success hinges on careful implementation and validation.

IV. RESULTS AND DISCUSSION

Demographic Characteristics

The survey targeted diverse stakeholders in Anambra State, including energy experts, policymakers, students and residents, to ensure a participatory approach. Table 4.1 summarizes the demographic profile of the 20 respondents. The sample is predominantly male (65%), urban (60%) and tertiary-educated (65%), with significant representation from energy experts (35%) and students (25%). Most respondents (80%) experience unreliable grid access and 85% rely on grid electricity, supplemented by diesel generators (50%) and biomass (20%). These findings reflect Anambra's energy challenges, including unreliable supply and fossil fuel dependence.

Table 4.1: Demographic Characteristics of Respondents

Variable	Category	Frequency	Percentage (%)
Gender (Q1)	Male	13	65.0
	Female	5	25.0
	Prefer not to say	2	10.0
Age Group (Q2)	18–25	9	45.0
	26–35	7	35.0
	36–45	1	5.0
	46–55	1	5.0
	56 and above	2	10.0
Location (Q3)	Urban (e.g., Awka, Onitsha, Nnewi)	12	60.0
	Rural	4	20.0
	Semi-urban	4	20.0
Occupation (Q4)	Energy Expert/Engineer	7	35.0
	Student	5	25.0
	Resident/Householder	4	20.0

	Policymaker/Government Official	3	15.0
	Industry/Business Owner	2	10.0
	Farmer	1	5.0
	Community Leader	1	5.0
	Other	2	10.0
Education Level (Q5)	Primary	1	5.0
	Secondary	2	10.0
	Tertiary	13	65.0
	Postgraduate	4	20.0
Grid Access (Q6)	Yes, reliable	3	15.0
	Yes, but unreliable	16	80.0
	No	1	5.0
Energy Source (Q7)	Grid electricity	17	85.0
	Diesel/petrol generator	10	50.0
	Biomass	4	20.0
	Solar	2	10.0
	Kerosene	1	5.0

Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP) was employed to prioritise seven decision criteria for renewable energy planning in Anambra State, Nigeria, addressing the study's objective to establish stakeholder-driven priorities for energy decision-making. The criteria, Cost-effectiveness (C1), Environmental sustainability (C2), Technical feasibility (C3), Social acceptability (C4), Job creation (C5), Energy access equity (C6) and Health impacts (C7), were evaluated using survey responses from 20 stakeholders, including energy experts, policymakers and residents. The results reflect Anambra's energy context, marked by unreliable grid supply and limited renewable adoption. Critically, the small sample size (n=20) and varying stakeholder familiarity (Q12, mean 3.6) may introduce variability, necessitating cautious interpretation for policy application. The prioritisation highlights technical and economic concerns, aligning with Anambra's urgent need for reliable energy, but lower weights for sustainability and equity suggest gaps in long-term planning awareness.

Pairwise Comparison Matrix

The pairwise comparison matrix was constructed using responses to Q13–Q19, which compared the seven criteria on Saaty's 9-point scale (1 = equally important, 9 = extremely more important, 1/9 = extremely less important). Geometric means aggregate responses to ensure robustness for ratio scales, as they mitigate the impact of extreme values. For Q13 (C1 vs. C2), responses (e.g., 5, 1/5, 1, 9) were aggregated using the geometric mean:

$$\left[GM = \sqrt[20]{x_1 \times x_2 \times \ldots \times x_{20}} \approx \sqrt[20]{15 \times \frac{1}{5} \times 1 \times 9 \times \ldots} \approx 3.22 \right]$$

This indicates cost-effectiveness (C1) is preferred over environmental sustainability (C2). Similar calculations were performed for Q14–Q19: Q14 (C1 vs. C3, ~0.43), Q15 (C2 vs. C4, ~2.71), Q16 (C3 vs. C5, ~3.98), Q17 (C4 vs. C6, ~2.34), Q18 (C5 vs. C7, ~3.22), Q19 (C1 vs. C6, ~2.71). Reciprocals ensured matrix consistency (e.g., C2 vs. C1 = 1/3.22). The 7x7 matrix (Table 4.3) reflects stakeholder priorities, with high values for technical feasibility (C3 vs. C5, 3.98) and cost-effectiveness (C1 vs. C2, 3.22), aligning with Anambra's need for reliable, affordable energy. However, the small sample (n=20) risks bias, particularly from expert-heavy respondents (Q4) and low familiarity (Q12) may skew sustainability judgments. The matrix's reliability hinges on stakeholder expertise, underscoring the need for broader sampling in future studies.

Criteria	C1	C2	C3	C4	C5	C6	C7
C1	1.00	3.22	0.43	0.37	0.25	2.71	0.31
C2	0.31	1.00	0.43	2.71	0.25	0.43	0.31
C3	2.34	2.34	1.00	0.37	3.98	2.34	0.31
C4	2.71	0.37	2.71	1.00	0.25	2.34	0.31
C5	4.00	4.00	0.25	4.00	1.00	0.43	3.22
C6	0.37	2.34	0.43	0.43	2.34	1.00	0.31

C7	3.22	3.22	3.22	3.22	0.31	3.22	1.00

Table 4.2: AHP Pairwise Comparison Matrix (Geometric Means)

Criteria Weights

Criteria weights were derived from the pairwise comparison matrix using the principal eigenvector, computed via the power method. An initial vector ([1, 1, 1, 1, 1, 1, 1]) was multiplied by the matrix iteratively (10 iterations for convergence), yielding: ([3.29, 1.64, 4.08, 2.60, 3.15, 1.68, 2.04]). Normalisation was performed:

$$w_i = \frac{v_i}{\sum v_i}$$

$\sum v_i$ = 3.29+1.64+4.08+2.60+3.15+1.68+2.04 ≈ 18.48

$$w_i = \frac{3.29}{18.48} = 0.18$$

Weights: C3 = 0.22, C1 = 0.18, C5 = 0.17, C4 = 0.14, C7 = 0.11, C2 = 0.09, C6 = 0.09 (Table 4.4). Technical feasibility (C3) and cost-effectiveness (C1) dominate, reflecting stakeholder priorities for reliable, affordable energy in Anambra's context of frequent outages and high costs (Q9, 80% unreliable grid, 35% high cost). Low weights for environmental sustainability (C2) and energy access equity (C6) suggest a pragmatic focus, potentially misaligned with Nigeria's sustainability goals. The small sample and expert dominance (Q4, 35%) may bias technical priorities, while low familiarity (Q12) risks underestimating sustainability.
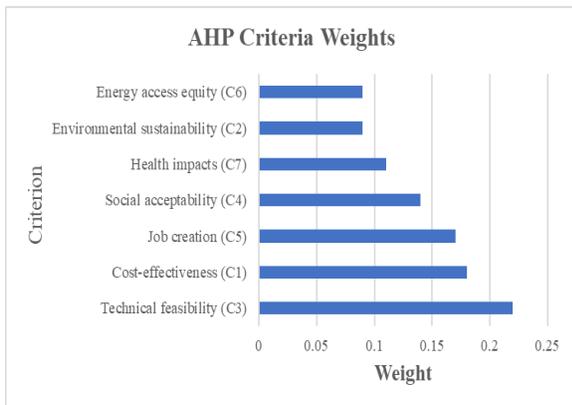

Figure 4.1: AHP Criteria Weights

Consistency Check

Consistency of the pairwise comparison matrix (Table 4.3) was verified to ensure reliable weights for the seven criteria: Cost-effectiveness (C1), Environmental sustainability (C2), Technical feasibility (C3), Social acceptability (C4), Job creation (C5), Energy access equity (C6) and Health impacts (C7). The principal eigenvalue (λ_{max}) was calculated by:

$$Aw = A \times w =$$

$$\begin{bmatrix} 1.00 & 3.22 & 0.43 & 0.37 & 0.25 & 2.71 & 0.31 \\ 0.31 & 1.00 & 0.43 & 2.71 & 0.25 & 0.43 & 0.31 \\ 2.34 & 2.34 & 1.00 & 0.37 & 3.98 & 2.34 & 0.31 \\ 2.71 & 0.37 & 2.71 & 1.00 & 0.25 & 2.34 & 0.31 \\ 4.00 & 4.00 & 0.25 & 4.00 & 1.00 & 0.43 & 3.22 \\ 0.37 & 2.34 & 0.43 & 0.43 & 2.34 & 1.00 & 0.31 \\ 3.22 & 3.22 & 3.22 & 3.22 & 0.31 & 3.22 & 1.00 \end{bmatrix}$$

$$x \begin{bmatrix} 0.18 \\ 0.09 \\ 0.22 \\ 0.14 \\ 0.17 \\ 0.09 \\ 0.11 \end{bmatrix} \approx \begin{bmatrix} 0.8967 \\ 0.7351 \\ 1.8249 \\ 1.5445 \\ 2.2579 \\ 0.9539 \\ 2.4811 \end{bmatrix}$$

The eigenvalue ratios were computed as:

$$\lambda_i = \frac{v_i}{w_i} \begin{cases} \lambda_1 = \frac{0.8967}{0.18} \\ \lambda_2 = \frac{0.7351}{0.09} \\ \lambda_3 = \frac{1.8249}{0.22} \\ \lambda_4 = \frac{1.5445}{0.14} \\ \lambda_5 = \frac{2.2579}{0.17} \\ \lambda_6 = \frac{0.9539}{0.09} \\ \lambda_7 = \frac{2.4811}{0.11} \end{cases}$$

However, $\lambda_{max} = \frac{\lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 + \lambda_5 + \lambda_6 + \lambda_7}{7} = 11.2741$

- Consistency Index (CI):

$$CI = \frac{\lambda_{max} - n}{n-1} = \frac{11.2741 - 7}{6} = 0.71235$$

- Consistency Ratio (CR):

$$CR = \frac{CI}{RI} = (0.71235/1.32) = 0.54$$

where (RI = 1.32) for (n=7).

The CR (≈0.5397) exceeds Saaty's threshold (0.1), indicating significant inconsistency likely due to the small sample size (n=20) and diverse stakeholder perspectives (Q4: 35% experts, 25% students). Low

familiarity (Q12: 15% slightly/not familiar) and complex criteria comparisons may contribute to erratic judgments.

Validation

Q20 validated AHP weights by asking respondents to select the most important criterion: Technical feasibility (25%, 5), Cost-effectiveness (20%, 4), Environmental sustainability (15%, 3), Energy access equity (15%, 3), Health impacts (15%, 3), Social acceptability (5%, 1), Job creation (5%, 1) (Table 4.5). These align with AHP weights (C3: 0.22, C1: 0.18), confirming stakeholder emphasis on reliability and affordability in Anambra's unreliable grid context. Lower rankings for sustainability (C2) and equity (C6) reflect Q20's distribution and suggest a pragmatic focus, potentially overlooking Nigeria's sustainability goals. The small sample limits statistical power and expert-heavy respondents (Q4, 35%) may bias technical priorities. Discrepancies (e.g., job creation's low Q20 ranking vs. 0.17 weight) indicate possible response inconsistencies, warranting larger samples for robustness. Validation supports AHP's applicability but highlights the need for stakeholder education on sustainability.

Criterion	Frequency	Percentage (%)
Technical feasibility (C3)	5	25.0
Cost-effectiveness (C1)	4	20.0
Job creation (C5)	1	5.0
Social acceptability (C4)	1	5.0
Health impacts (C7)	3	15.0
Environmental sustainability (C2)	3	15.0
Energy access equity (C6)	3	15.0

Table 4.3: AHP Validation (Q20)

TOPSIS Analysis: Alternative Ranking

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) was applied to rank renewable energy alternatives for Anambra State, Nigeria, addressing the study's objective to identify optimal energy sources based on stakeholder preferences. The alternatives are Solar photovoltaic (PV) systems (A1), Biomass (A2), Small-scale hydropower (A3) and Wind energy (A4), with wind replacing natural gas (Q24) due to its non-renewable nature, likely a survey error. Wind energy suits Anambra's occasional high wind speeds. Responses from 20 stakeholders (Q21–Q24) on a 5-point Likert scale were analysed, using AHP weights from Section 4.4: Technical feasibility (C3: 0.22), Cost-effectiveness (C1: 0.18), Job creation (C5: 0.17), Social acceptability (C4: 0.14), Health impacts (C7: 0.11), Environmental sustainability (C2: 0.09) and Energy access equity (C6: 0.09). TOPSIS ranks alternatives by proximity to the positive ideal solution (PIS) and distance from the negative ideal solution (NIS). The small sample (n=20) and high AHP CR (0.5397, Section 4.4.3) limit generalizability, while the single-question survey design (Q21–Q24) oversimplifies criteria interactions. Results inform Anambra's energy planning, emphasising solar due to abundant resources (Q12, 50% solar preference).

Decision Matrix

The TOPSIS decision matrix was constructed using mean scores from Q21–Q24 for Solar (A1), Biomass (A2), Hydropower (A3)ss and Wind (A4, replacing natural gas). Scores (1 = Not suitable, 5 = Highly suitable) were aggregated:

$$\frac{1}{20} \sum_{j=1}^{20} S_j$$

Calculated Mean Scores:

- Solar (A$_1$) demonstrated the highest suitability:

$$x_1 = \frac{89}{20} = 4.45 \ (SD = 0.60)$$

With 85% of responses ≥4 and no scores below 3, indicating strong consensus about its viability. The relatively small standard deviation suggests consistent positive perceptions across respondents.

- Hydropower (A$_3$) showed moderate suitability:

$$x_2 = \frac{61}{20} = 3.05 \ (SD=1.10)$$

The bimodal distribution (peaks at 3 and 4) reflects divergent views, potentially tied to respondents' awareness of site-specific constraints.

- Biomass (A$_2$) scored lower:

$$x_2 = \frac{49}{20} = 2.45 \text{ (SD=1.05)}$$

The presence of both minimum (1) and maximum (5) scores indicates polarisation, possibly reflecting differing assessments of feedstock availability.

- Wind (A$_4$) received the lowest mean:

$$x_2 = \frac{44}{20} = 2.20 \text{ (SD=1.41)}$$

The uniform distribution across all possible scores suggests fundamental disagreements about wind potential in the study area.

Alternative	Mean Score
Solar (A1)	4.45
Biomass (A2)	2.45
Hydropower (A3)	3.05
Wind (A4)	2.20

Table 4.4: TOPSIS Decision Matrix (Mean Scores)

Solar's high score (4.45) reflects abundant irradiation and stakeholder preference (Q12, 50% solar). Biomass (2.45) and Wind (2.20) score low, indicating limited resources or awareness (Q11, Q12). Hydropower's moderate score (3.05) aligns with Anambra's limited water resources. The single-question design aggregates all criteria, reducing granularity, while the small sample (n=20) and low familiarity (Q12, 15% slightly/not familiar) limit precision.

Normalised and Weighted Decision Matrix

To facilitate comparative analysis across criteria, the decision matrix was normalised using the Euclidean norm method. The normalisation process transforms disparate measurement scales into dimensionless values, ensuring equitable comparison. The normalised score r_i for each alternative was computed as:

$$r_i = \frac{x_i}{\sqrt{\sum_{i=1}^4 x_i^2}}$$

The denominator, representing the Euclidean norm of the raw scores, was calculated as follows:

$$\sqrt{(4.45^2 + 2.45^2 + 3.05^2 + 2.2^2)} = 6.3204$$

Subsequently, the normalised scores for each renewable energy alternative were derived:

$r_{solar} = 0.7042$, $r_{Biomass} = 0.3876$, $r_{Hydro-power} = 0.4826$, $r_{wind} = 0.3481$

Due to the survey's single-question structure (Q21–Q24), the Analytical Hierarchy Process (AHP) weights (C3: 0.22, C1: 0.18, C5: 0.17, C4: 0.14, C7: 0.11, C2: 0.09, C6: 0.09) could not be applied individually. Consequently, a uniform weighting approach was adopted, with the average weight w_{avg} calculated as:

$$w_{avg} = \frac{0.22 + 0.18 + \cdots + 0.09}{7} = 0.1429$$

The weighted scores v_i were then determined by multiplying each normalised score by w_{avg}:

$v_{Solar} = 0.1006$, $v_{Biomass} = 0.0554$, $v_{hydro-power} = 0.0690$, $v_{wind} = 0.0497$

Table 4.5 presents the complete normalised and weighted matrix. While normalisation enables cross-criterion comparability, the use of an average weight introduces methodological limitations. Specifically, it fails to account for the disproportionate influence of technical feasibility (C3) and cost-effectiveness (C1), which were prioritised by stakeholders (Section 4.4). Furthermore, the AHP's high consistency ratio (CR = 0.5397) and the small sample size (n=20), with 35% of respondents being sector experts (Q4), may introduce bias. Additionally, wind energy's reliance on repurposed natural gas data introduces uncertainty, potentially limiting the applicability of these findings for Anambra's energy strategy.

Alternative	Normalized Score	Weighted Score
Solar (A1)	0.7042	0.1006
Biomass (A2)	0.3876	0.0554
Hydropower (A3)	0.4826	0.0690
Wind (A4)	0.3481	0.0497

Table 4.5: Normalised and Weighted Decision Matrix

Ideal Solutions and Ranking Analysis

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) was employed to rank the renewable energy alternatives based on their proximity to optimal performance. The positive ideal solution (PIS, V^+) and negative ideal solution (NIS, V^-) were determined from the weighted scores:

$V^+=$ max(vi) = 0.1006(Solar), V^- = min(vi) = 0.0497(Wind)

The Euclidean distances from each alternative to PIS (S_i^+) and NIS (S_i^-) were calculated as:

$$S_i^+ = \sqrt{(v_i - V^+)^2}, S_i^- = \sqrt{(v_i - V^-)^2}$$

The computations yielded the following results:

- Solar (A1):
$S_1^+ = 0$ (identical to PIS),

$S_1^- \approx 0.0509$

- Biomass (A2):
$S_2^+ \approx 0.0452$

$S_2^- \approx 0.0057$

- Hydropower (A3):
$S_3^+ \approx 0.0316$

$S_3^- \approx 0.0193$

- Wind (A4):
$S_4^- \approx 0.0509$

$S_4^- = 0$ (identical to NIS)

The closeness coefficient (CC_i) for each alternative was computed to determine relative performance:

$$CC_i = \frac{S_i^-}{S_i^+ + S_i^-}$$

The resulting CC_i values and corresponding rankings are presented in Table 4.6. Solar energy (A1) achieved the highest possible score (CC_1=1.0000), indicating perfect alignment with the ideal solution,

followed by Hydropower (A3, CC_3=0.3792), Biomass (A2, CC_2=0.1120) and Wind (A4, CC_4=0.00).

Alternative	S_i^+	S_i^-	CC_i	Rank
Solar (A1)	0.0000	0.0509	1.0000	1
Hydropower (A3)	0.0316	0.0193	0.3792	2
Biomass (A2)	0.0452	0.0057	0.1120	3
Wind (A4)	0.0509	0.0000	0.0000	4

Table 4.6: TOPSIS Ranking Results

V. CONCLUSION

This study demonstrated the efficacy of MCDA in addressing Anambra State's energy planning complexities. By prioritising solar PV and biomass through a stakeholder-driven framework, the research provides a roadmap for achieving SDG 7 while acknowledging the need for equitable and sustainable solutions. However, bridging the gap between policy ambitions and on-the-ground implementation requires robust governance, inclusive stakeholder engagement and continuous methodological refinement. As Nigeria navigates its energy transition, MCDA offers a transformative lens to harmonise technical feasibility, economic viability and socio-environmental justice, a critical step toward a resilient energy future.

VI. RECOMMENDATIONS

To operationalise the findings of this study and advance sustainable energy planning in Anambra State, the state government should establish structured participatory mechanisms, such as community workshops and public consultations, to co-develop energy priorities and criteria weights for MCDA applications. Also, the Anambra State government, in collaboration with national agencies like the Nigerian Meteorological Agency and the Rural Electrification Agency, should invest in updating and digitising energy-related datasets, such as solar irradiance maps, biomass resource inventories and demand profiles. Additionally, the state should prioritise capacity-building programs, including training for policymakers and planners on MCDA tools and sensitivity analysis. Finally, the state should use pilot projects in urban centers like

Onitsha and rural areas should test this framework to refine its applicability.

REFERENCES

[1] Acuto, M., & Rayner, S. (2016). City networks: Breaking gridlocks or forging (new) lock-ins? International Affairs, 92(5), 1147–1166.

[2] Al-Amin, M. (2014). Domestic energy crisis and deforestation challenges in Nigeria. https://www.cabidigitallibrary.org/doi/full/10.5555/20143156427

[3] Algarín, C. R., Llanos, A. P., & Castro, A. O. (2017). An Analytic Hierarchy Process Based Approach for Evaluating Renewable Energy Sources. International Journal of Energy Economics and Policy, 7, 38–47.

[4] Al-Kurdi, N., Pillot, B., Gervet, C., & Linguet, L. (2019). Towards Robust Scenarios of Spatio-Temporal Renewable Energy Planning: A GIS-RO Approach. In T. Schiex & S. De Givry (Eds.), Principles and Practice of Constraint Programming (Vol. 11802, pp. 729–747). Springer International Publishing. https://doi.org/10.1007/978-3-030-30048-7_42

[5] Asthana, S., Gibson, A., Moon, G., & Brigham, P. (2003). Allocating resources for health and social care: The significance of rurality: Resource allocation and rurality. Health & Social Care in the Community, 11(6), 486–493. https://doi.org/10.1046/j.1365-2524.2003.00454.x

[6] Barrera-Zapata, M., Zuñiga-Cortes, F., & Caicedo-Bravo, E. (2023). A Framework for Evaluating Renewable Energy for Decision-Making Integrating a Hybrid FAHP-TOPSIS Approach: A Case Study in Valle del Cauca, Colombia. Data, 8(9), 137.

[7] Brans, J. P., & Vincke, Ph. (1985). Note—A Preference Ranking Organisation Method: (The PROMETHEE Method for Multiple Criteria Decision-Making). Management Science, 31(6), 647–656. https://doi.org/10.1287/mnsc.31.6.647

[8] Chang, H.-K., Liou, J.-C., & Chen, W.-W. (2012). Protection priority in the coastal environment using a hybrid ahp-topsis method on the Miaoli coast, Taiwan. Journal of Coastal Research, 28(2), 369–374.

[9] Ciuriak, D. (2018). Frameworks for Data Governance and the Implications for Sustainable Development in the Global South. Available at SSRN 3266113. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3266113

[10] Clements, B., Coady, D., Fabrizio, S., Gupta, S., & Shang, B. (2014). Energy subsidies: How large are they and how can they be reformed? Economics of Energy & Environmental Policy, 3(1), 1–18.

[11] Clemmons-Brown, C. A. (2023). Innovation and evidence-based Decision-Making: Addressing New Graduate nurse turnover. Nursing Administration Quarterly, 47(1), E1–E11.

[12] Deshmukh, S. C. (2013). Preference ranking organisation method of enrichment evaluation (promethee). International Journal of Engineering Science Invention, 2(11), 28–34.

[13] Deverka, P. A., Lavallee, D. C., Desai, P. J., Armstrong, J., Gorman, M., Hole-Curry, L., O'Leary, J., Ruffner, B., Watkins, J., Veenstra, D. L., Baker, L. H., Unger, J. M., & Ramsey, S. D. (2012). Facilitating comparative effectiveness research in cancer genomics: Evaluating stakeholder perceptions of the engagement process. Journal of Comparative Effectiveness Research, 1(4), 359–370. https://doi.org/10.2217/cer.12.36

[14] Dupont, E., Koppelaar, R., & Jeanmart, H. (2020). Global available solar energy under physical and energy return on investment constraints. Applied Energy, 257, 113968.

[15] Ellis, G., & Ferraro, G. (2017). The social acceptance of wind energy: Where we stand and the path ahead. https://pure.qub.ac.uk/en/publications/the-social-acceptance-of-wind-energy-where-we-stand-and-the-path-

[16] Ezenekwe, U., Nwokoye, E., Metu, A., & Kalu, D. C. U. (2014). Efficiency of Nigeria's Electricity Market: Emerging Issues, Prospects and Challenges. Association of Energy and Environmental Economics of Nigeria-Nigerian Journal of Energy and Environmental Economics, 6(1), 105–121.

[17] Ezzati, M., Bailis, R., Kammen, D. M., Holloway, T., Price, L., Cifuentes, L. A., Barnes, B., Chaurey, A., & Dhanapala, K. N. (2004). ENERGY MANAGEMENT AND GLOBAL HEALTH. Annual Review of Environment and Resources, 29(1), 383–419. https://doi.org/10.1146/annurev.energy.29.062 103.121246

[18] Frangopoulos, C. A., & Keramioti, D. E. (2010). Multi-criteria evaluation of energy systems with sustainability considerations. Entropy, 12(5), 1006–1020.

[19] Heinemann, G., Banzer, F., Dumitrescu, R., Hirschhausen, C. V., Neuhoff, M. E., & Nwadiaru, V. O. (2022). Transforming electricity access by replacing back-up generators with solar systems: Recent trends and evidence from Nigeria. Renewable and Sustainable Energy Reviews, 157, 111751.

[20] Hou, G., Chen, T., Ma, K., Liao, Z., Xia, H., & Yao, T. (2019). Improving social acceptance of waste-to-energy incinerators in China: Role of place attachment, trust and fairness. Sustainability, 11(6), 1727.

[21] Ikejemba, E. C., & Schuur, P. (2016). Locating solar and wind parks in South-Eastern Nigeria for maximum population coverage: A multi-step approach. Renewable Energy, 89, 449–462.

[22] Jack, J., & Jack, B. (2022). Nigeria's Energy Crisis and the Sustainability Question. Social and Health Sciences, 20(1 and 2). https://doi.org/10.25159/2957-3645/11449

[23] Janković, R., Mihajlović, I., & Amelio, A. (2019). Time Series Vector Autoregression Prediction of the Ecological Footprint based on Energy Parameters (No. arXiv:1910.11800). arXiv. https://doi.org/10.48550/arXiv.1910.11800

[24] Kabeyi, M. J. B., & Olanrewaju, O. A. (2023). The levelized cost of energy and modifications for use in electricity generation planning. Energy Reports, 9, 495–534.

[25] Kaya, T., & Kahraman, C. (2011). Multicriteria decision making in energy planning using a modified fuzzy TOPSIS methodology. Expert Syst. Appl., 38, 6577–6585. https://doi.org/10.1016/j.eswa.2010.11.081

[26] Liu, Y., Sun, C., Xia, B., Cui, C., & Coffey, V. (2018). Impact of community engagement on public acceptance towards waste-to-energy incineration projects: Empirical evidence from China. Waste Management, 76, 431–442.

[27] Madanchian, M., & Taherdoost, H. (2023). A comprehensive guide to the TOPSIS method for multi-criteria decision making. Madanchian M, Taherdoost H. A Comprehensive Guide to the TOPSIS Method for Multi-Criteria Decision Making. Sustainable Social Development, 1(1), 2220.

[28] Maroto, C., Segura, M., Ginestar, C., Uriol, J., & Segura, B. (2012). Aggregation of Stakeholder Preferences in Sustainable Forest Management using AHP. ICORES, 100–107. https://pdfs.semanticscholar.org/4afc/b22cd98 23f8a7cd5f74c526702219b755a5d.pdfMartine z, L. J.,

[29] Lambert, J. H., & Karvetski, C. W. (2011). Scenario-informed multiple criteria analysis for prioritising investments in electricity capacity expansion. Reliability Engineering & SystemSafety, 96(8), 883–891.

[30] Miller, C. A., Iles, A., & Jones, C. F. (2013). The Social Dimensions of Energy Transitions. Science as Culture, 22(2), 135–148. https://doi.org/10.1080/09505431.2013.78698 9

[31] Montibeller, G., & von Winterfeldt, D. (2015). Biases and debiasing in multi-criteria decision analysis. 2015 48th Hawaii International Conference on System Sciences, 1218–1226. https://ieeexplore.ieee.org/abstract/document/ 7069955/

[32] Okoye, P. U., Ezeokonkwo, J. U., & Nworji, G. C. (2017). Sustainability of Renewable Sources of Energy for Rural Communities in Anambra State. Advances in Energy and Power(CEASE PUBLICATION), 5(4), 37–47. https://doi.org/10.13189/aep.2017.050401

[33] Oladigbolu, J. O., Ramli, M. A., & Al-Turki, Y. A. (2020). Optimal design of a hybrid PV solar/micro-hydro/diesel/battery energy system for a remote rural village under tropical climate conditions. Electronics, 9(9), 1491.Patnaik, R. (2018). Impact of industrialisation on environment and sustainable solutions–reflections from a south Indian region. IOP Conference Series: Earth and Environmental Science, 120, 012016. https://iopscience.iop.org/article/10.1088/1755-1315/120/1/012016/meta

[34] Pinto, N. N. (2013). Technologies for Urban and Spatial Planning: Virtual Cities and Territories: Virtual Cities and Territories (Vol. 2326). IGI Global. https://books.google.com/books?hl=en&lr=&id=vd1GAwAAQBAJ&oi=fnd&pg=PR1&dq=Technologies+for+Urban+and+Spatial+Planning:+Virtual+Cities+and+Territories+N.+Pinto&ots=0LsthntRKd&sig=jPwqfReG1_7y8byq1k_WQ2y89d8

[35] Podvezko, V., & Podviezko, A. (2010). dependence of multi-criteria evaluation result on choice of preference functions and their parameters / daugiakriterinių vertinimų rezultatų priklausomybė nuo prioritetų funkcijų ir jų parametrų PASIRINKIMO. Technological and Economic Development of Economy, 16(1), 143–158. https://doi.org/10.3846/tede.2010.09

[36] Porzsolt, F., Wiedemann, F., Becker, S. I., & Rhoads, C. J. (2019). Inclusion and exclusion criteria and the problem of describing homogeneity of study populations in clinical trials. BMJ Evidence-Based Medicine, 24(3), 92–94.

[37] Poveda, C. A., & Lipsett, M. G. (2013). Weighting sustainable development indicators (SDIs) for surface mining operations using the analytical hierarchy process (AHP). International Journal of the Analytic Hierarchy Process, 5(2). https://www.ijahp.org/index.php/IJAHP/article/view/199

[38] Ramík, J. (2017). Ranking alternatives by pairwise comparisons matrix and priority vector. Scientific Annals of Economics and Business, 64(Special), 85–95.

[39] Roumell, E. A., Todoran, C., & Salajan, F. D. (2020). A Framework for Capacity Building in Adult and Workforce Education Programming. Adult Literacy Education, 2(2), 16–32.

[40] Ruzieva, M., & Ruziev, U. (2024). Assessing environmental problems: Primary indicators and their role in ecosystem management. E3S Web of Conferences, 587, 02012. https://www.e3s-conferences.org/articles/e3sconf/abs/2024/117/e3sconf_greenenergy24_02012/e3sconf_greenenergy24_02012.html

[41] Saat, M. (2000). An approach to multi-objective decision making: Analytical hierachy. Gazi University Faculty of Economics and Administrative Journals, 2(2), 149–162.

[42] Saaty, T. L. (1990). Multicriteria Decision Making: The Analytic Hierarchy Process. AHP Series I/RWS Publication.

[43] Shrestha, R. M., & Acharya, J. S. (2015). Sustainable energy access planning: A framework. Asian Development Bank. https://books.google.com/books?hl=en&lr=&id=SnggCwAAQBAJ&oi=fnd&pg=PT8&dq=Sustainable+Energy+Access+Planning:+A+Framework+Jiwan+Acharya&ots=o_Us3L-HMS&sig=zOYExIT_r0Wgt9rK62XKXah4IwI

[44] Stache, F., & Sydow, J. (2023). Breaking a Path by Creating a New One: How Organisational Change Boosts Children's Cancer Care. Organisation Studies, 44(3), 351–376. https://doi.org/10.1177/01708406221103965

[45] Vincent-Akpu, I. (2012). Renewable energy potentials in Nigeria. IAIA12 Conference

Proceedings: Energy Future, The Role of Impact Assessment 32nd Annual Meeting of the International Association for Impact Assessment, 1–6.

[46] Woo, M. (2008). Multi Criteria Decision Analysis (MCDA).