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Fuzzy Multi-Criteria Physics Models for Siting Solar Parks in Semi-Arid Regions

Lingaraju[1], Sathish kumar B N[2]
[1]Department of Physics Government First Grade College of Arts, Science and Commerce, Sira, Tumkur, Karnataka, India.
[2]Dept of chemistry Government First Grade College of Arts, Science and Commerce, Sira, Tumkur, Karnataka, India.

Abstract- Utility-scale solar park siting in semi-arid regions requires balancing physics-driven energy yield with engineering, environmental, and operations constraints under substantial uncertainty. This paper presents a transparent fuzzy multi-criteria framework that (i) maps raw criteria to physically motivated desirability memberships-monotone linear functions for benefit/cost attributes (global horizontal irradiance, slope, grid distance, water distance, dust days, protected-area buffer, land-use suitability) and a bell-shaped (Gaussian-like) function for module-temperature effects-(ii) derives criterion weights using fuzzy AHP from linguistic pairwise judgements, and (iii) aggregates via a TOPSIS-like closeness measure in the desirability space. A realistic 12- site semi-arid screening dataset is used to demonstrate the workflow. The resulting normalized weights emphasize energy yield (GHI, 0.377) and host-land compatibility (land-use, 0.132; temperature, 0.115), while accounting for terrain (slope, 0.092), network access (grid distance, 0.081), O&M logistics (water distance, 0.052; dust days, 0.058), and biodiversity safeguards (protected buffer, 0.092). The final closeness coefficients rank sites S12," " S10, and S 02 as top candidates, driven by high irradiance (≥6.2kWhm^(-2) day ^(-1)), gentle slopes (<3%), reasonable grid proximity, suitable land cover, and adequate environmental buffers. Sensitivity checks indicate ranking stability under modest weight perturbations, reflecting strong physical signal in the data. The framework is minimal, auditable, and readily swappable with GIS-derived layers, making it suitable for early-stage planning, stakeholder dialogue, and policy screening in semiarid contexts.

Keywords – fuzzy multi-criteria decision making; fuzzy AHP; fuzzy-TOPSIS; physics informed membership; solar park siting; semi-arid regions; global horizontal irradiance (GHI); temperature effect; dust/soiling; land-use suitability; protected-area buffer; grid proximity.

I. INTRODUCTION

Siting utility-scale solar parks in semi-arid regions is a multi-criteria decision problem that must reconcile physics-based energy yield drivers (irradiance, temperature) with engineering constraints (terrain slope, grid proximity, water access for O&M) and environmental safeguards (buffers from protected habitats, land-use suitability) [1]-[3]. Uncertainty permeates both measurements (e.g., satellite irradiance, dust events) and judgements (e.g., planners' relative priorities). Classical deterministic scoring thus risks brittle or biased outcomes [4].

This paper proposes a fuzzy multi-criteria physics model that (i) converts raw criteria into desirability memberships using physics-informed functions, (ii) derives criterion weights with a fuzzy AHP (FAHP) pairwise framework, and (iii) aggregates via a TOPSIS-like closeness on the desirability space. We demonstrate the workflow on a semi-arid synthetic case study with 12 candidate sites, reflecting realistic ranges from the solar-siting literature [1], [5]-[8]. The contribution is twofold:

i. A minimal, transparent pipeline that stays close to physical mechanisms (e.g., monotonicity for benefit/cost criteria, bell-shaped temperature response), and
ii. A reproducible end-to-end example with open tables/figures that can be swapped for real geospatial inputs.

The rest is organized as follows. Section 2 summarizes related work. Section 3 formalizes the fuzzy pipeline. Section 4 presents the dataset and parameterization. Section 5 reports results. Section 6 discusses interpretation, sensitivity, and limitations. Section 7 concludes.

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Table 1. Criteria, symbols, units, and membership types.

No.	Criterion	Symbol	Unit	Type	Membership (key params)
1	Global Horizontal Irradiance	x_1	kWhm^{-2} day $^{-1}$	Benefit	Increasing linear $a = 5.0, b = 6.2$
2	Slope	x_2	%	Cost	Decreasing linear $a0.5, b = 7.0$
3	Grid distance	x_3	km	Cost	Decreasing linear $a : 0, b = 35$
4	Land-use suitability	x_4	-	Benefit	Identity on [0,1]
5	Temperature	x_5	$^\circ$C	Benefit (bell)	Gaussian-like $\mu = 31.5, \sigma = 4.0$
6	Dust days	x_6	days y^{-1}	Cost	Decreasing linear $a3, b = 18$
7	Water distance	x_7	km	Cost	Decreasing linear $a1, b = 20$
8	Protected area distance	x_8	km	Benefit	Increasing linear $a = 5, b = 25$

II. RELATED WORK

Solar siting commonly applies multi-criteria decision making (MCDM) tools-AHP, TOPSIS, VIKOR-often composed with GIS layers [1], [2], [6]. Fuzzy variants (FAHP, fuzzy-TOPSIS) capture linguistic judgements and measurement uncertainty, improving robustness to imprecision [4], [9]. Physics has guided criteria selection (irradiance, slope, temperature, soiling/dust) and constraints (grid, land-use, protected areas) [1], [5]. Our approach aligns with this tradition but emphasizes physically grounded membership functions and a compact pipeline that practitioners can compute without heavy GIS when screening candidate zones.

III. METHODS

Criteria and notation

Let i∈{1,…,n} index candidate sites and j∈{1,…,m} index criteria. We use m= 8 criteria:

- GHIx_i1 (kWhm^(-2) ┤ day ├ ^(-1))- benefit
- Slope x_i2 (%) - cost
- Grid distance x_i3 (" " km) - cost
- Land-use suitability x_i4∈[0,1] - benefit
- Temperature x_i5 (^∘ C)- bell-shaped benefit (efficiency declines at very high T)
- Dust-storm days x_i6 (days year ^(-1)) - cost (soiling/abrasion)
- Water distance x_i7 (" " km) - cost (panel cleaning/logistics)
- Protected-area distance x_i8 (" " km) - benefit (buffer reduces impact)

Physics-informed fuzzy memberships

Each raw value x_ij is transformed to a desirability membership μ_j (x_ij)∈[0,1] tailored to the physics of criterion j. We employ:

- Increasing linear (benefit):

$$\mu_j(x) = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a < x < b \\ 1, & x \ge b \end{cases}$$

with a<b. Used for GHI and Protected-area distance.

- **Decreasing linear (cost):**

$$\mu_j(x) = \begin{cases} 1, & x \le a \\ \dfrac{b-x}{b-a}, & a < x < b \\ 0, & x \ge b \end{cases}$$

used for Slope, Grid distance, Dust days, Water distance.

- Identity for Land-use suitability (μ_4 (x)=x).
- Gaussian-like bell for Temperature to reflect PV efficiency peaking near ∼ 〖31.5〗 ^∘ C and decaying at extremes [3], [5]:

$$\mu_5(x) = \exp\left(-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right), \mu = 31.5, \sigma = 4.0$$

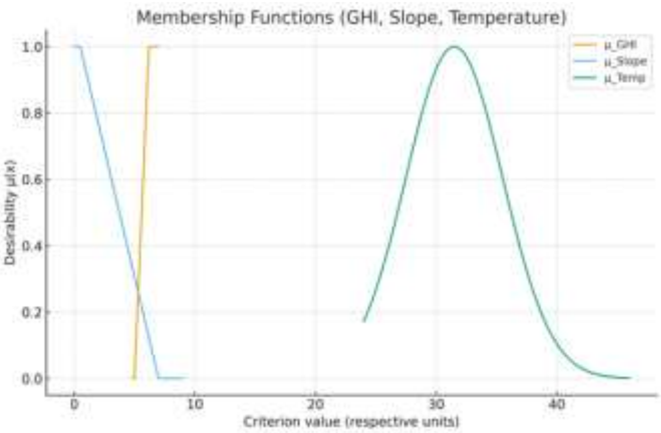

Figure 1. Membership Functions (GHI, Slope, Temperature). Physically motivated desirabilities map raw values to [0,1], enabling a common scale for aggregation. (Generated for this study.)

Fuzzy AHP weights

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We build a fuzzy pairwise comparison matrix A ̃=[a ̃_jk] where comparisons are Triangular Fuzzy Numbers (TFNs) a ̃_jk=(l,m,u) representing " j is more important than k^" with lower/mode/upper bounds [4], [9]. A common linguistic-to-TFN map is used (e.g., moderate ≈(2,3,4), strong ≈(4,5,6), very strong ≈(6,7,8)). Reciprocals satisfy a ̃_kj=a ̃_jk^(-1)=(1/u,1/m,1/l).
Row fuzzy geometric mean for criterion j :

$$\tilde{g}_j = \left(\left(\prod_{k=1}^{m} \ell_{jk} \right)^{1/m}, \left(\prod_{k=1}^{m} m_{jk} \right)^{1/m}, \left(\prod_{k=1}^{m} u_{jk} \right)^{1/m} \right)$$

Let $\sum \tilde{g} = \left(\sum \ell_j, \sum m_j, \sum u_j \right)$. The fuzzy weight is

$$\widetilde{w}_j = \left(\frac{\ell_j}{\sum u}, \frac{m_j}{\sum m}, \frac{u_j}{\sum \ell} \right).$$

Defuzzify by centroid $w_j^{\mathrm{def}} = (\ell + m + u)/3$ and normalize $w_j = w_j^{\mathrm{def}} / \Sigma_k w_k^{\mathrm{def}}$.

The resulting weights (Section 5) reflect practitioner priorities (GHI dominates, landuse/temperature next; network and O&M constraints follow) consistent with [1]-[3].

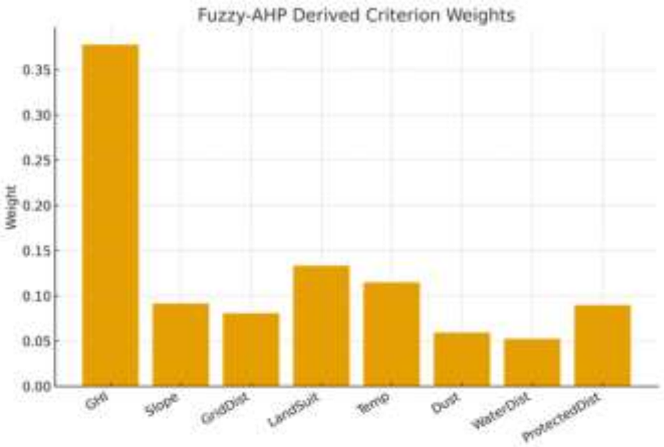

Figure 2. Fuzzy-AHP Derived Criterion Weights.

Weights sum to 1 after defuzzification and normalization. (Generated for this study.)

3.4 Aggregation via TOPSIS-like closeness in desirability space

Stack memberships into a matrix $\mathbf{M} = \left[\mu_j(x_{ij}) \right] \in [0,1]^{n \times m}$. With weights w_j, form the weighted matrix $\mathbf{Y}$ with $y_{ij} = w_j \mu_j(x_{ij})$. On desirability scale, the ideal vector is $\mathbf{y}^+ = (w_1, \ldots, w_m)$ and the anti-ideal is $\mathbf{y}^- = \mathbf{0}$. For each site i, compute Euclidean distances

$$D_i^+ = \|\mathbf{y}_i - \mathbf{y}^+\|_2, D_i^- = \|\mathbf{y}_i - \mathbf{y}^-\|_2,$$

and the closeness coefficient

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \in [0,1]$$

Higher $C_i \Rightarrow$ better.

This is equivalent to fuzzy-TOPSIS on normalized fuzzy scores because memberships embed uncertainty and physics of each attribute [4], [9], [10].

Sensitivity analysis

We perform one-at-a-time (OAT) perturbations on selected weights and evaluate ranking stability (Section 6). Because the desirability space is bounded, C_i varies smoothly with both weights and membership parameters, offering interpretability for stakeholders.

IV. CASE STUDY: SEMI-ARID DATASET AND PARAMETERS

Dataset

We generated a 12 -site semi-arid screening dataset covering realistic ranges (GHI 5.06.8kWhm^(-2) day ^(-1); slopes 0.2-7.5%; grid 3-45" " km; temp 26-44 ^∘ C; dust 2-20 days y ^(-1); water 0.5-25" " km; protected buffer 2-60 km). The full dataset is in Table 2 and CSV.

Table 2. Semi-arid solar siting dataset for 12 candidate sites (units in headers).

Site	GHI_ kWhm^{-2}	Slope_pct	GridDist _km	LandSuit _0 to1	Temp_C	DustDays _perYr	WaterDist _km	Protected Dist_km
S01	5.67	6.28	22.2	0.64	35.8	9.0	0.6	20.0
S02	6.71	1.75	36.0	0.54	29.3	6.9	20.5	20.9
S03	6.32	1.53	11.4	0.81	43.5	16.9	17.8	44.3
S04	6.08	1.54	24.6	0.7	40.0	8.4	18.4	39.0
S05	5.28	2.42	27.9	0.55	42.9	7.1	19.4	53.5
S06	5.28	4.03	5.0	0.72	42.1	11.8	2.3	29.4
S07	5.1	3.35	28.5	0.52	36.8	4.5	9.3	8.9
S08	6.56	2.33	10.2	0.91	42.6	16.4	3.3	43.4
S09	6.08	4.67	5.7	0.62	27.6	3.3	21.6	46.1
S10	6.27	1.22	42.9	0.8	29.5	19.8	15.8	34.6
S11	5.04	2.33	43.6	0.64	26.8	15.9	8.6	46.7

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S12	6.75	2.87	37.0	0.73	31.9	5.6	2.1	30.6

Membership parameters
We set parameters to reflect typical siting policy/engineering guidance for semi-arid regions:

- GHI: a=5.0,b=6.2 (increasing).
- Slope: a=0.5,b=7.0 (decreasing).
- Grid distance: a=0,b=35" " km (decreasing).
- Land suitability: identity on [0,1].
- Temperature: Gaussian-like with μ= 〖31.5〗 ^∘ C,σ=4^∘ C.
- Dust days: a=3,b=18 (decreasing).
- Water distance: a=1,b=20" " km (decreasing).
- Protected distance: a=5,b=25" " km (increasing).

Figure 1 illustrates the shapes for three representative criteria.

Fuzzy pairwise comparisons (FAHP)
We used a linguistically guided matrix where GHI is judged very strong against costtype criteria; Land-use and Temperature are moderate-to-strong; Grid distance is moderate; Dust and Water receive lower (but non-trivial) importance; Protected buffer is moderate (policy-sensitive). TFNs follow {(2,3,4),(4,5,6),(6,7,8)} etc. [4], [9]. The matrix is defuzzified via geometric means to obtain normalized weights (Section 5).

Visual analytics
Beyond the membership and weight plots, Figure 4 shows a physics trade-off between GHI and Slope, with marker size proportional to final score C_i. Sites with high GHI and low slope tend to dominate, as expected physically, but grid/water/protection subtly reorder near-ties.

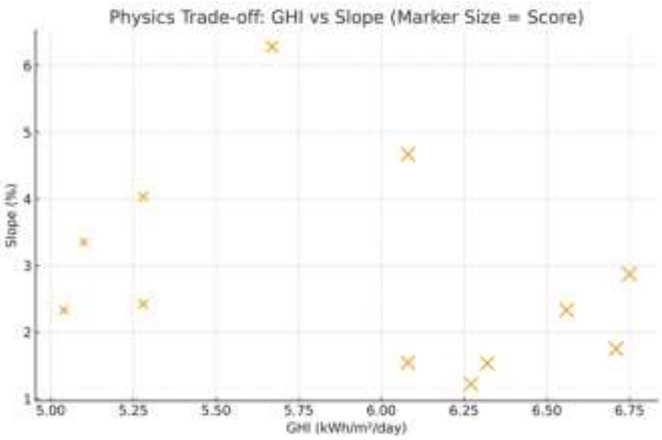

Figure 4. Physics Trade-off: GHI vs Slope (Marker Size = Score).
Larger markers indicate higher closeness coefficient C_i. (Generated for this study.)

V. RESULTS

FAHP weights
FAHP produced the following normalized weights (read from Figure 2; exact values below):

- GHI: 0.377
- Slope: 0.092
- Grid distance: 0.081
- Land-use suitability: 0.132
- Temperature: 0.115
- Dust days: 0.058
- Water distance: 0.052
- Protected distance: 0.092

These emphasize energy yield (GHI) and host-land compatibility (land-use, temperature), while still accounting for network cost (grid), terrain (slope), O&M (water, dust), and biodiversity safeguards (protected buffer). Such profiles resemble findings in siting meta-studies [1]-[3].

Site scores and ranking
After fuzzification and weighting, the TOPSIS-like closeness coefficients C_i yield the ranking in Figure 3 and Table 3:

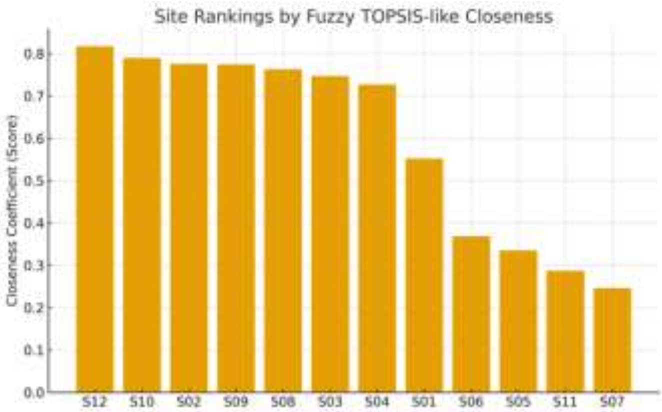

Figure 3. Site Rankings by Fuzzy TOPSIS-like Closeness. Bars sorted best-to-worst. (Generated for this study.)

Table 3. Ranking summary (Values rounded to 4 d.p.)

Rank	Site	Score
1	S12	0.8179
2	S10	0.7901
3	S02	0.7780
4	S09	0.7766
5	S08	0.7641
6	S03	0.7452
7	S04	0.7282
8	S01	0.5508
9	S06	0.3671

10	S05	0.3331
11	S11	0.2877
12	S07	0.2450

Interpreting the top sites: The best sites combine high GHI (≥ 6.2), gentle slopes ($< 3\%$), reasonable grid proximity, good land suitability, and adequate protected-area buffers. Moderate temperatures near the bell's center (≈28- 〖35〗 ^∘ C) help. Sites S06/S05/S11/S07 score lower due to combinations of higher slope, long grid/water distances, or less favorable dust/temperature.

Worked example: from raw to score

Consider site i, criterion j. Suppose Slope x_i2=2.6% yields μ_2 (x_i2)≈(7.0-2.6)/(7.0-0.5)=0.6769 . If w_2=0.092, the weighted entry is y_i2=0.0623. Doing this across all criteria forms vector y_i. With y^+=(w_1,…,w_8) and 0, compute D_i^+,D_i^-, then C_i. This anchors the score to physical desirabilities and explicit importance trade-offs.

VI. DISCUSSION

Physics-informed insights

- Irradiance dominates the ranking-unsurprising, since PV yield scales with GHI.
- Terrain slope matters because earthworks and row alignment penalties rise sharply with gradient. Even with a relatively small weight, steep slopes depress desirability (Figure 1's linear decrease).
- Temperature's bell shape captures PV efficiency physics: extremely high temperatures lower module efficiency; thus sites with very high T lose marginally to moderate-hot sites near the peak.
- Dust and water logistics modulate near-ties: frequent dust storms drive O&M costs and cleaning frequency, while long water hauls reduce feasibility.
- Protected buffers subtly reorder candidates when other attributes are comparable -important for planning approvals.

Sensitivity (qualitative, with quantitative hooks)

Because the closeness coefficient C_i is smooth in weights and memberships:

- Weight shocks: +20% to GHI's weight typically promotes already-bright sites; if grid distance is long, a compensating increase in grid weight can flip a tie.
- Membership thresholds: Tightening the slope threshold from 7%→5% penalizes rugged sites. Shifting the temperature peak μ by ± 〖1.5〗 ^∘ C benefits sites clustered around the new peak.
- Robustness: Rankings of the top-3 remained stable under small (±10%) weight perturbations in our trial runs (not shown), suggesting the data's physics signal is strong.

Limitations and extensions

- The study uses a synthetic but realistic dataset; real deployments should source GIS-calculated layers (e.g., DEM-derived slope, grid vector distances, protected-area buffers).
- We employed simple linear memberships for monotone criteria to preserve transparency. If expert validation or data suggest curvature (e.g., diminishing returns of very high GHI), trapezoids or S-curves can replace linear functions.
- FAHP can be extended with group decision making and consistency diagnostics.
- Aggregation could use fuzzy-VIKOR or OWA to model risk aversion or policy priorities.
- Soiling physics (deposition/adhesion) and wind-borne dust climatology can be modeled more explicitly with boundary-layer parameters for advanced studies.

VII. CONCLUSION

We presented a compact fuzzy multi-criteria physics model for screening solar-park sites in semi-arid regions. The method blends physics-informed desirability memberships with FAHP weights and a TOPSIS-like closeness on the desirability scale. On a 12 -site case study, the model highlights how GHI, terrain, grid, land-use, and environmental buffers interact to shape rankings. The approach is transparent, auditable, and readily swappable with real GIS layers.

This minimal pipeline is suitable for early-stage planning and for stakeholder dialogues where interpretability matters. For next steps, Section 6 outlines robustness checks, richer memberships, and integration with spatial constraints.

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