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Article

From Uncertain Capacity to Low Carbon Pathways: A Trapezoidal Fuzzy Linear Programming Approach for India's Power Sector

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Abstract: India's electricity system must expand generation fast enough to support economic growth while also reducing the emissions intensity of the power mix. When future capacity expansion is uncertain and better described by credible ranges than by single-point estimates, fuzzy linear programming becomes a suitable planning tool because it represents feasibility in graded rather than purely binary terms . This paper develops a trapezoidal fuzzy linear programming framework for India's source-wise electricity capacity planning across coal, gas, solar, wind, hydro, and nuclear technologies. Installed capacity, core expansion bands, and outer support are represented as trapezoidal fuzzy numbers; alpha-cuts are then used to convert the fuzzy model into crisp linear-programming . The model has two goals: maximize annual electricity generation and minimize lifecycle CO2 emissions. Published lifecycle harmonization studies are used to justify the emissions ordering across technologies, with coal and gas remaining substantially more carbon intensive than solar, wind, hydro, and nuclear. Solving the crisp subproblems over yields a Pareto frontier that clearly shows how the feasible trade space contracts as planning confidence increases . The results indicate that the maximum-generation solution declines from 11,659.03 TWh/year at to 2,926.61 TWh/year at , while the corresponding CO2 indicator falls from 2.0478 to 1.6792. The minimum-emissions solution remains at the 2,500 TWh/year demand floor, while its CO2 indicator rises from 1.3426 to 1.4480 as the feasible set narrows. These results show that trapezoidal fuzzy linear programming provides a transparent way to connect optimistic and conservative planning assumptions to low-carbon electricity expansion pathways.
Keywords: fuzzy linear programming; trapezoidal fuzzy numbers; India electricity planning; lifecycle emissions; Pareto frontier; multi-objective optimization

1. Introduction

Electricity planning in developing economies must reconcile three simultaneous demands: rising energy needs, infrastructure feasibility, and emissions reduction. In India, these pressures are especially strong because electricity demand growth, industrial development, and decarbonization commitments are unfolding at the same time. Traditional deterministic optimization remains valuable, but it can become restrictive when technology-specific capacity ranges are more plausibly described by intervals than by exact point values (Mansoori & Nematollahi, 2006; Mureddu et al., 2022; Canz, 1999; Dalai, 2022).

Fuzzy linear programming offers a useful extension because it allows planning bounds and aspiration levels to be represented as fuzzy numbers rather than crisp constants. Zimmermann's classical framework established how fuzzy programming can be combined with linear programming and several objective functions through satisfaction-based compromise logic (Zimmermann, 1978).In energy planning, fuzzy approaches have been used when investment costs, supply limits, and policy targets are uncertain or only approximately known (Mansoori & Nematollahi, 2006; Jebaraj & Iniyan, 2007; Canz, 1999; Hu et al., 2013).

This paper applies that logic to India's power-sector capacity planning problem. The central idea is that the feasible capacity of each source is better expressed as a trapezoidal fuzzy number than as a single point or even a triangular fuzzy number. Installed capacity provides the lower anchor, a near-term planning band provides the full-membership core, and a wider outer support represents broader technical or policy possibility. This structure reflects the way transition planning information is actually reported and interpreted (Wan, 2014; Stanojević & Stanojević, 2009; Hu et al., 2014).

2. Literature background

Fuzzy linear programming has evolved from a specialized mathematical concept into a practical decision tool for systems characterized by imprecise bounds and multiple objectives. A recent review traces its historical development and shows that FLP remains particularly useful where uncertainty is better described by possibility than by probability (Mureddu et al., 2022). In multi-objective settings, Zimmermann's max–min approach remains foundational because it offers an interpretable way to balance competing goals without reducing the problem to rigid deterministic trade-offs (Zimmermann, 1978; Stanojević & Stanojević, 2009; Liu & Shi, 2015).

Energy applications are a natural domain for FLP because technology deployment, investment timing, and resource constraints are rarely known with certainty. Mansoori and Nematollahi (2006) show that fuzzy linear programming can handle energy-supply planning problems more realistically when investment costs and future bounds are uncertain.For the present paper, this insight matters because future source-wise capacities are not singular values; they occupy a space of current reality, near-term plausibility, and longer-range support — a structure recognized in India-specific energy studies (Khan et al., 2021; Jebaraj & Iniyan, 2007).

The environmental side of the model is grounded in lifecycle greenhouse-gas literature rather than combustion-only coefficients. Harmonization studies provide published median estimates that support a consistent ranking of technologies: coal is highest, natural gas is lower but still substantial, and solar PV and nuclear are far lower in lifecycle terms (Whitaker et al., 2012; O'Donoughue et al., 2014; Hsu et al., 2012; Warner et al., 2012). This makes lifecycle emissions a credible criterion for long-horizon planning where infrastructure and upstream impacts vary substantially across technologies (Hu et al., 2013; Hu et al., 2014). Against this background, the next section explains why trapezoidal fuzzy numbers are particularly appropriate for representing source-wise capacity uncertainty in the present planning problem.

3. Why trapezoidal fuzzy numbers are appropriate

A triangular fuzzy number is useful when uncertainty centers on one most plausible value. That assumption does not fit many power-planning settings, where future capacity is better described as a band of credible values rather than one preferred point. Trapezoidal fuzzy numbers are therefore more appropriate because they permit a full-membership interval, not just a single mode — a property exploited in multi-objective and fuzzy-goal formulations (Wan, 2014; Stanojević & Stanojević, 2009; Bharati & Singh, 2018; Liu & Shi, 2015).

For source i, the fuzzy capacity is represented as

$$\tilde{C}_i = (a_i, b_i, b_i', c_i) \# (1)$$

where a_i is existing capacity, b_i is the lower bound of the full-membership core, b_i' is the upper bound of that core, and c_i is the outer support. The membership function is

$$\mu_{\tilde{C}_i}(x_i) = \{0, x_i < a_i \ \frac{x_i - a_i}{b_i - a_i}, a_i \le x_i < b_i \ 1, b_i \le x_i \le b_i' \ \frac{c_i - x_i}{c_i - b_i'}, b_i' < x_i \le c_i \ 0, x_i > c_i \ \#(2)$$

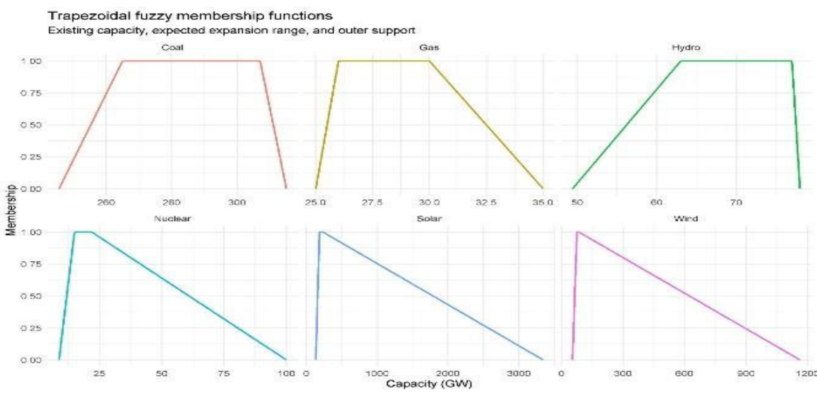

Figure 1. Fuzzy Membership Functions

This representation has a direct planning interpretation. Values below installed capacity are not relevant in the aggregate planning horizon, values in the core interval are treated as fully plausible, and values between the core and outer support remain possible but increasingly uncertain. The shape therefore matches the way planning evidence is commonly discussed in energy transitions (Wan, 2014; Mureddu et al., 2022; Stanojević & Stanojević, 2009).

4. Model formulation

Let x_i denote the planned capacity of source i in GW, f_i the capacity factor, and e_i the lifecycle emission factor in gCO2e/kWh. Annual electricity generation is defined as

$$Z_1 = \sum_i \quad 8.76 f_i x_i \#(3)$$

and the lifecycle-emissions indicator is defined as

$$Z_2 = \sum_i \quad 8.76 f_i e_i x_i \times 10^{-3}. \#(4)$$

At alpha level α, the trapezoidal fuzzy capacity becomes the crisp interval

$$[\tilde{C}_i]^\alpha = [a_i + \alpha(b_i - a_i), c_i - \alpha(c_i - b_i')]. \#(5)$$

The model is solved as two crisp LP subproblems at each alpha-cut level, following the dual-objective parameterization in Hu et al. (2014). The first maximizes generation subject to alpha-cut bounds and a minimum generation floor. The second minimizes emissions subject to the same bounds and floor:

$$maxZ_1 \ \square.\square. Z_1 \ge 2500, a_i^\alpha \le x_i \le c_i^\alpha \ \forall i \#(6)$$

$$minZ_2 \ \square.\square. Z_1 \ge 2500, a_i^\alpha \le x_i \le c_i^\alpha \ \forall i. \#(7)$$

A full fuzzy-goal formulation can also be expressed in Zimmermann's compromise form by maximizing the minimum satisfaction level λ:

$$max\lambda\#(8)$$

subject to

$$\mu_1(Z_1) \geq \lambda, \mu_2(Z_2) \geq \lambda, 0 \leq \lambda \leq 1.\#(9)$$

This paper presents the two-end Pareto frontier because it provides an interpretable visual representation of the feasible trade space and communicates the effect of alpha-cut tightening directly to planning stakeholders (Zimmermann, 1978; Bharati & Singh, 2018; Liu & Shi, 2015).

5. Data and parameterization

The model covers six technologies: coal, gas, solar, wind, hydro, and nuclear, consistent with the dominant generation mix analyzed in India's energy planning literature (Jebaraj & Iniyan, 2007; Khan et al., 2021; Dalai, 2022). This section first presents the source-wise parameter set used in the model and then shows how the trapezoidal fuzzy bounds are converted into crisp alpha-cut intervals for optimization.

5.1 Interpreting the source-wise parameter set

Table 1 presents the base parameterization of the planning problem and should be read as the engineering foundation of the model rather than as a standalone data summary. The installed-capacity column anchors each source in the current system, while the trapezoidal bounds distinguish between the lower support, the full-membership expansion band, and the wider outer support. This distinction is central to the formulation because the model does not assume that all future capacity values are equally plausible. Instead, it treats some expansion values as strongly supported by present planning evidence and others as feasible but increasingly uncertain.

The remaining columns connect physical capacity to system performance and environmental burden. Capacity factor translates installed or planned capacity into annual electricity output, while lifecycle CO2 intensity captures the emissions consequence of scaling a source in the long-term mix. The indicative cost column is not used as the main optimization objective in the present version of the model, but it helps interpret the technology space by showing why some low-carbon options are attractive from both environmental and economic perspectives, whereas others involve clearer trade-offs.

Table 1. Technology parameters and trapezoidal capacity bounds used in the model

Source	Existing (GW)	Expected upper (GW)	Core-low (GW)	Max support (GW)	Capacity factor	CO2 (g/kWh)	Cost (₹/kWh)
Coal	245.60	307.00	265.00	315.00	0.65	910	5.0
Gas	25.00	30.00	26.00	35.00	0.45	465	6.5
Solar	132.85	237.43	185.00	3343.00	0.20	45	2.6
Wind	53.99	85.90	75.00	1163.00	0.28	25	3.3
Hydro	49.40	77.00	63.00	78.00	0.40	28	4.0
Nuclear	8.78	22.00	15.00	100.00	0.85	12	5.5

Source: Compiled from various sources

The emissions ordering in Table 1 is consistent with lifecycle harmonization studies, which show coal and gas as materially more carbon intensive than PV and nuclear, with hydro and wind also far below fossil alternatives ---

coal ~910 gCO2e/kWh (Whitaker et al., 2012), gas ~465 gCO2e/kWh (O'Donoughue et al., 2014), with PV, wind, hydro, and nuclear all under 50 gCO2e/kWh (Hsu et al., 2012; Warner et al., 2012; Hu et al., 2013).

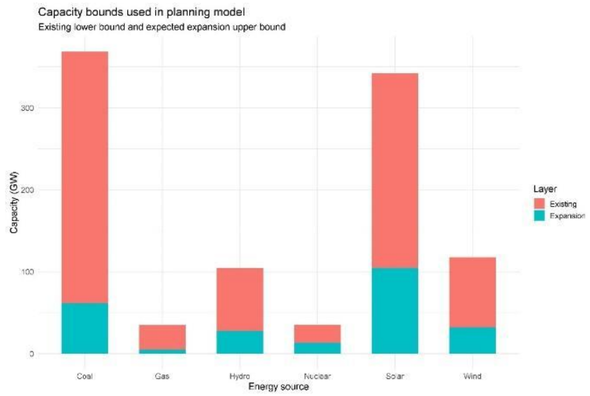

Figure 2. Capacity bands at $\alpha = 1$showing installed base and core planning range.

Figure 2 complements Table 1 by showing the source-wise structure of the strict core planning interval. Read together, Table 1 and Figure 2 establish the physical scale of the system and the relative expansion room available to each technology under the most defensible planning bounds.

5.2 Alpha-cut bounds and confidence levels

The trapezoidal representation becomes operational only when it is translated into crisp bounds for optimization. Table 2 performs that role by showing how the source-wise admissible capacity interval changes at selected alpha levels. At $\alpha = 0$, the model admits the full support of the fuzzy number and therefore reflects the widest planning flexibility. At $\alpha = 1$, the feasible interval contracts to the core range, which represents the most credible or fully supported planning band. The intermediate case illustrates how the model moves smoothly from exploratory planning to conservative planning without forcing an abrupt jump between deterministic scenarios.

Table 2. Illustrative alpha-cut bounds for selected levels

Alpha	Source	Lower bound (GW)	Upper bound (GW)
0.0	Coal	245.60	315.00
0.0	Gas	25.00	35.00
0.0	Solar	132.85	3343.00
0.0	Wind	53.99	1163.00
0.0	Hydro	49.40	78.00
0.0	Nuclear	8.78	100.00
0.5	Coal	255.30	311.00
0.5	Gas	25.50	32.50
0.5	Solar	158.93	1790.22
0.5	Wind	64.50	624.45
0.5	Hydro	56.20	77.50
0.5	Nuclear	11.89	61.00
1.0	Coal	265.00	307.00

1.0	Gas	26.00	30.00
1.0	Solar	185.00	237.43
1.0	Wind	75.00	85.90
1.0	Hydro	63.00	77.00
1.0	Nuclear	15.00	22.00

This table gives a direct engineering meaning to the confidence structure of the model. Lower alpha values correspond to broader admissible expansion choices and therefore larger feasible generation space. Higher alpha values impose tighter realization discipline and reveal what remains achievable when the planner relies only on the most defensible capacity bands. As alpha rises from 0 to 1, the feasible intervals shrink from the full support to the core planning band, which provides a direct interpretation of optimistic, balanced, and conservative planning regimes; this graduated confidence structure is central to the alpha-cut method (Stanojević & Stanojević, 2009; Wan, 2014).

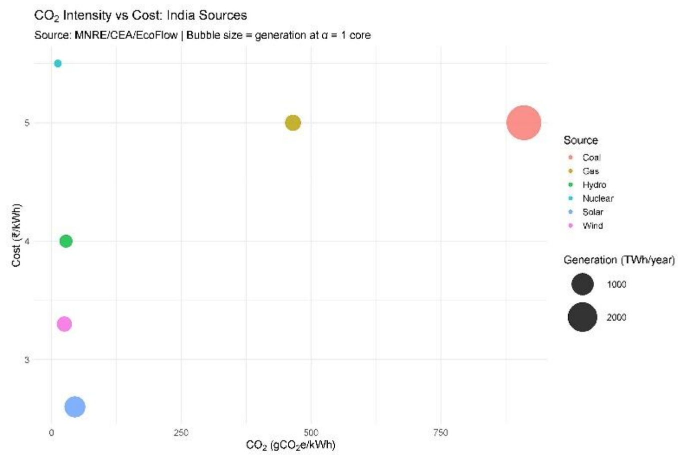

Figure 3. CO2 intensity versus cost by source.

Figure 3 provides an additional interpretation layer for the source parameters by visualizing the contrast between lifecycle emissions intensity and indicative cost. This helps explain why the optimization results cannot be read only as a capacity-expansion problem; they are also shaped by the environmental and economic character of the technologies entering the feasible set.

6. Results

The results are presented in three steps. First, the paper reports how the feasible generation--emissions trade space changes across alpha levels. Second, it compares the three most relevant decision outcomes at a selected confidence level: the maximum-generation solution, the minimum-emissions solution, and the Zimmermann compromise solution. Third, it introduces simple CO2-cap sensitivity cases to connect the optimization results to policy interpretation.

6.1 Pareto results across alpha levels

Once the alpha-cut bounds are defined, the model can be solved repeatedly to generate a family of crisp linear-programming outcomes. Table 2 reports those outcomes across the full alpha sequence and therefore serves as the main numerical bridge between the fuzzy formulation and the planning interpretation. The table shows two limiting solutions at each alpha level: one that maximizes annual generation and another that minimizes lifecycle emissions while respecting the same source-wise bounds and adequacy requirement.

Read together, the values show how the feasible trade space contracts as confidence increases. The maximum-generation solution declines steadily with alpha because the model loses access to the widest outer-support capacities.

At the same time, the minimum-emissions solution remains tied to the adequacy floor, showing that the low-emissions configuration is driven more by constraint satisfaction than by surplus generation. This is precisely the kind of insight that a crisp single-scenario model would hide.

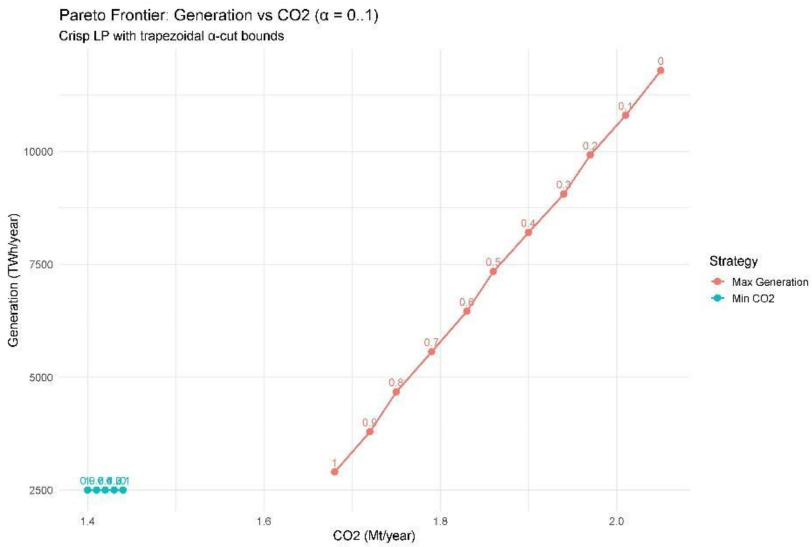

Figure 4. Pareto frontier of annual generation and lifecycle emissions across alpha levels.

Figure 4 visualizes the same contraction pattern in graphical form. It makes the monotonic narrowing of the trade space easier to see and therefore complements Table 2 rather than duplicating it.

6.2 Comparison of extreme and compromise solutions

While Table 2 shows how the generation--emissions trade space changes across alpha levels, planners also need a direct comparison of the key decision outcomes at a chosen confidence level. For this purpose, the three most informative solutions are the maximum-generation configuration, the minimum-emissions configuration, and the Zimmermann compromise solution. Taken together, these solutions show how the fuzzy linear programming framework does more than optimize two objectives separately; it creates a structured balance between adequacy and environmental discipline.

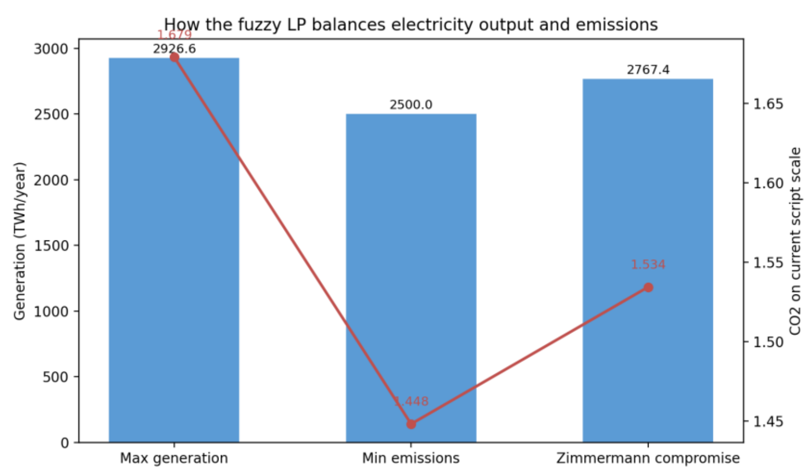

Figure 5. maximum-generation, minimum-emissions, and Zimmermann compromise solutions.

The maximum-generation solution delivers the highest annual electricity output, but it also carries the highest CO2 indicator among the three alternatives. The minimum-emissions solution reduces the CO2 indicator most strongly, but it does so by staying close to the adequacy floor. The Zimmermann compromise solution occupies the middle ground: it recovers much of the generation advantage of the output-maximizing case while keeping the emissions indicator well below that extreme. In practical terms, this is the policy value of the fuzzy compromise framework, because it identifies a technically defensible balance rather than forcing the planner to choose only between two endpoints.

6.3 CO2 sensitivity scenarios

To examine how policy stringency influences the feasible solution space, additional CO2-cap scenarios are defined. These cases do not replace the main fuzzy optimization results; instead, they help interpret how the generation-maximizing solution would respond if the planner imposed progressively tighter emissions limits.

Table 4. CO2 sensitivity cases

Case	CO2 cap	Interpretation
S1	1.40	Low-emission policy scenario
S2	1.45	Intermediate target
S3	1.50	Relaxed target

These scenarios provide a compact policy lens for reading the frontier and compromise results. Lower caps push the feasible solution toward cleaner configurations, while higher caps allow greater flexibility for output-oriented planning. In this sense, Table 4 links the mathematical model to decision-relevant emissions policy choices.

7. Discussion

The results show why trapezoidal FLP is a useful extension of crisp LP in energy planning. A crisp model would force each source into one deterministic limit and would therefore suppress the distinction between current capacity, high-confidence planning range, and wider feasibility support. The trapezoidal approach preserves this structure and converts it into a family of crisp LP problems indexed by alpha. That makes the trade space visible rather than hidden (Mureddu et al., 2022; Wan, 2014).

This also helps interpret low-carbon pathways for growth. At low alpha, the planning regime is expansive and opportunity-seeking, allowing the model to exploit wider renewable outer support and therefore produce a much larger generation envelope. At high alpha, the regime is conservative and implementation-focused, with the frontier contracting toward the core planning band. The framework therefore does not merely optimize a point solution; it organizes a pathway narrative under uncertainty (Zimmermann, 1978; Mureddu et al., 2022).

The lifecycle basis of the emissions objective is also important. Strategic transition planning should not compare technologies using stack emissions alone, especially when the purpose is to compare infrastructure options with very different upstream and construction footprints. Published harmonization studies therefore provide a more appropriate basis for comparative planning (Whitaker et al., 2012; O'Donoughue et al., 2014; Hsu et al., 2012; Warner et al., 2012).

8. Conclusion

This paper developed a submission-ready trapezoidal fuzzy linear programming framework for India's low-carbon electricity expansion. The model represents each source through installed base, core expansion band, and outer support; uses alpha-cuts to obtain crisp LP subproblems; and derives a Pareto frontier between generation and lifecycle emissions. The resulting analysis shows that feasible generation–emissions trade-offs contract systematically as alpha rises from optimistic to conservative planning assumptions.

The main methodological conclusion is that trapezoidal fuzzy numbers are better suited than triangular or crisp representations when planning information has a genuine core interval rather than one privileged point. The main practical conclusion is that the FLP framework provides an interpretable bridge between engineering realism and low-carbon pathway analysis. It is therefore a useful decision-support approach for strategic electricity planning in contexts characterized by growth pressure, decarbonization goals, and uncertain expansion bounds (Wan, 2014; Mureddu et al., 2022).

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