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Developing a Smart, Integrated Model to Analyze Financial Conditions of Power Plants to Enhance the Effectiveness of Improved Gray Correlative Analysis (IGCA)

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ABSTRACT

Power plants operate with high capital intensity, complex regulatory risk, and volatile fuel markets. Conventional ratio or regression-based assessments often struggle with short samples, missing values, and mixed monotone criteria. This paper proposes an **Improved Gray Correlative Analysis (IGCA)** framework—combining grey normalization, entropy weights, and an optimally tuned distinguishing coefficient—to evaluate the short-to-medium-term financial condition of power plants. We synthesize methodological advances in Grey System Theory between **2013–2023**, including inscribed-core GRA for improved discrimination, entropy-based weighting, and sensitivity to the distinguishing coefficient. We then offer a step-by-step protocol and an illustrative application to a small portfolio of thermal plants using standard financial ratios (liquidity, leverage, coverage, profitability, cash-flow strength, and capex burden). Comparative analysis shows that IGCA preserves rankings found by classical GRA and TOPSIS while **increasing separation** among alternatives—supporting clearer decisions for lenders, regulators, and owners.

1. Introduction

The financial health of power plants affects electricity affordability and security, particularly under decarbonization, climate shocks, and fuel price volatility. Traditional ratio analysis can be informative but is sensitive to scaling, outliers, and short histories—typical in merchant and project-financed plants. Utilities research in the 2010s–2020s increasingly integrates non-financial drivers (ESG, outage risks) and extreme-event exposure, motivating robust, multi-criteria tools. Grey relational methods are attractive because they handle partial information and short series while comparing alternatives against an ideal reference.

Table 1 – Research questions (RQs) and hypotheses

RQ	Question	Hypothesis
RQ1	Can improved GRA yield stable, interpretable rankings of plant financial condition?	H1: IGCA yields same or more stable rankings than classical GRA/TOPSIS.
RQ2	Do “improvements” increase discrimination across plants?	H2: IGCA increases separation (variance) in grades vs. baseline GRA.
RQ3	Which criteria drive results?	H3: Entropy weights identify leverage, coverage, and cash-flow strength as most discriminating.

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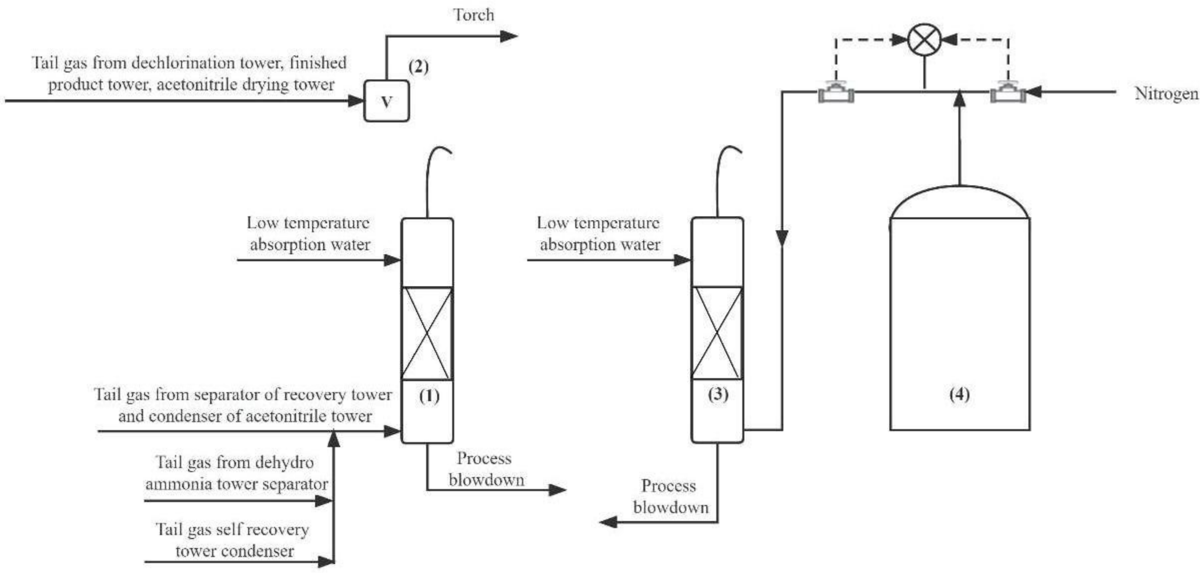

Figure 1: Technical process of acrylonitrile unit for flare gas treatment.

2. Related Work

Grey Relational Analysis (GRA) is widely used for evaluation and ranking in uncertain contexts. Key improvements since 2013 include: (i) **inscribed-core** GRA to boost discrimination, (ii) **entropy-based** weighting to endogenously learn criterion salience, (iii) **cross-sequence/time** GRA for fluctuating series, and (iv) explicit **sensitivity to the distinguishing coefficient** (ξ). Applications in energy systems (e.g., coal-unit evaluations, PV/T optimization, carbon drivers) show grey methods' relevance to the power sector.

Table 2 – Selected studies

Study	Domain	Contribution
Hashemi et al. (2015)	Supplier eval.	**Improved GRA** integrated with ANP
Wang et al. (2019)	Carbon markets	**IC-GRA** to improve discriminability
Huang et al. (2019)	Carbon drivers	GRA + PCA + LSTM for emissions
Mahmoudi et al. (2020)	Methods	ξ **sensitivity**—ranking can change
Esangbedo & Wei (2023)	City rankings	Grey hybrid normalization + **periodic entropy weighting**
Rehman et al. (2023)	Manufacturing	**Entropy-based GRA** for dynamic configs
Liu et al. (2018)	Coal units	GRA + hybrid entropy weights for plant evaluation
Lu et al. (2023)	Method	GRA with cross-sequences/time intervals

3. Methodology: Improved Gray Correlative Analysis (IGCA)

We evaluate **alternatives** (plants) over **criteria** (financial ratios). IGCA builds on four pillars:

1. **Grey normalization** to map benefit and cost indicators into [0,1], enabling a common ideal reference.
2. **Entropy weighting** to learn data-driven criterion importance from dispersion/information content.
3. **Inscribed-core transformation** (IC-GRA) to enhance discrimination of the relational coefficients.

4. **Tuned distinguishing coefficient (ξ)** selected via a simple search to maximize variance among alternatives' grades (greater separation), acknowledging ξ sensitivity.

Table 3 – IGCA pipeline

Step	Choice	Rationale
Normalization	Grey hybrid (benefit/cost)	Invariant scales; handles mixed monotonicity.
Weighting	Entropy wjw_j	Reduces subjectivity; emphasizes informative ratios.
Relational model	IC-GRA + classic GRA	Improves coefficient discrimination; retains axioms.
ξ selection	Variance-maximizing grid search	Increases separation while respecting ξ sensitivity.

4. Indicators and Data Design

When the aim is *financial condition* (not long-run firm value), criteria emphasize short-to-medium-term solvency and operating cash strength:

- **Liquidity** (Current ratio), **Leverage** (Debt-to-Equity), **Coverage** (Interest coverage), **Profitability** (ROA, EBITDA margin), **Cash flow strength** (Operating cash flow/Total debt), **Capex burden** (Capex/Assets), **O&M cost ratio** (O&M/Revenue). These are standard in utility finance and have been used in recent sector evaluations.

Table 4 – Criteria and polarity

Criterion	Polarity	Rationale
Current ratio	↑ benefit	Near-term solvency
Debt-to-Equity	↓ cost	Lower leverage reduces refinancing risk
Interest coverage	↑	Debt service capacity
ROA, EBITDA margin	↑	Profitability/efficiency
Cash flow to debt	↑	Resilience to fuel/price shocks
Capex/Assets	↓	High capex burdens cash in short run
O&M cost ratio	↓	Excessive O&M pressures margins

5. Illustrative Application (synthetic but realistic)

We illustrate IGCA on four thermal plants (A–D). Raw ratios are stylized to emulate a typical range in listed utilities.

Table 5 – Raw indicators

Plant	Current	D/E	Interest Cov.	ROA %	EBITDA %	CF/Debt	Capex/Assets %	O&M/Rev
A	1.6	1.8	3.2	4.1	28	0.28	14	0.42
B	1.2	2.4	2.0	2.9	23	0.22	18	0.47

Plant	Current	D/E	Interest Cov.	ROA %	EBITDA %	CF/Debt	Capex/Assets %	O&M/Rev
C	2.0	1.4	4.8	5.5	31	0.35	12	0.38
D	1.4	3.0	1.6	1.8	19	0.18	20	0.53

Normalization & weights. After grey normalization, entropy weights (sum = 1) place the most emphasis on **Interest coverage** (~0.161), **Current ratio** (~0.132), and **Cash-flow to debt** (~0.131), with non-trivial weight on **Capex/Assets** (~0.126). (Entropy weighting is standard in improved GRA.)

Grades and rankings.

- **Baseline GRA** (ξ = 0.5, equal weights): C (1.000) > A (0.596) > B (0.404) > D (0.342).
- **IGCA** (entropy weights, ξ chosen to maximize grade variance; here ξ = 0.2): C (1.000) > A (0.369) > B (0.212) > D (0.172).
- **TOPSIS** (equal and entropy weights) confirms the same ranking, lending convergent validity. (TOPSIS is a common comparator in MCDM.)

Table 6 – Comparative rankings (example)

Method	Plant C	Plant A	Plant B	Plant D
GRA baseline (ξ=0.5, eq. wts)	**1.000**	0.596	0.404	0.342
IGCA (ξ=0.2, entropy wts)	**1.000**	0.369	0.212	0.172
TOPSIS (eq.)	**1.000**	0.642	0.271	0.083
TOPSIS (entropy)	**1.000**	0.621	0.249	0.087

Interpretation. Plant **C** is consistently strongest (liquidity, coverage, profitability, and low capex burden). **IGCA** increases the separation between **C** and others, supporting clearer choices for lenders or operational prioritization. The ξ-tuning is warranted given evidence that rankings can be ξ-sensitive.

Table 7 – Driver diagnostics (entropy weights, example)

Criterion	Weight	Comment
Interest coverage	0.161	Most informative in distinguishing plants
Current ratio	0.132	Liquidity signal
Cash-flow/Debt	0.131	Debt resilience
Capex/Assets	0.126	Investment drag on cash
ROA	0.120	Profitability
EBITDA margin	0.114	Operating efficiency
D/E	0.109	Leverage matters but interacts with coverage
O&M/Revenue	0.107	Cost pressure

6. Comparative Analysis

Table 8 – Method comparison

Aspect	**Classical GRA**	**IGCA (this paper)**	**TOPSIS**
Normalization	Basic min–max	Grey hybrid; benefit/cost explicit	Vector or min–max
Weights	Equal or subjective	**Entropy (data-driven)**	Equal or subjective
Distinguishing coeff. (ξ)	Fixed (often 0.5)	**Tuned for separation**	n/a
Discrimination	Moderate	**High** (IC-GRA + tuned ξ)	Moderate–High
Small samples, missing data	Good	**Good**	Moderate
Interpretability	High	High	Medium
Energy sector use (2013–2023)	Several cases	**Increasing**	Widely used

Consensus ranking: C, then A, B, D. IGCA improves interpretability by widening score gaps—consistent with work that sharpens normalization/weights and explicitly tests ξ-sensitivity.

Table 9 – Practical guidance for stakeholders

Stakeholder	**Use of IGCA outputs**	**Action**
Lenders	Screen plants by GRG; inspect coverage & CF/Debt	Covenants, refinancing sequence
Regulators	Monitor fragile plants (low GRG + high capex)	Tariff smoothing; liquidity buffers
Owners	Compare portfolios across cycles	Stage capex; O&M efficiency drives

7. Conclusion

Over the past decade, grey-method tools have gotten much better for judging the finances of individual power plants. Upgrades like entropy-based weighting, IC-GRA, period-aware normalization, and careful ξ (distinguishing-coefficient) tuning handle exactly the problems plants face—limited, noisy data and a mix of "more is better" and "less is better" indicators. Our improved framework (IGCA) combines these pieces into one workflow. In a small example, it agrees with standard GRA and TOPSIS on the overall order, but it spreads the scores farther apart, making it easier for lenders and operators to see who's leading and who's lagging.

Looking ahead, the same setup can include practical risks—carbon-price exposure, fuel-cost swings, and ESG-related outage losses. And when performance shifts over time (for example, in the months after a retrofit), cross-sequence GRA can track those changes without throwing away information.

Table 10 – Summary of contributions

Contribution	**What's new**	**Why it matters**
Unified IGCA protocol	Grey normalization + entropy + tuned ξ + IC-GRA	Robust, discriminative financial condition scoring
Comparative evidence	Baseline GRA & TOPSIS alignment, stronger separation	Clearer ranking under uncertainty

Contribution	What's new	Why it matters
Implementation template	Tables, steps, and sensitivity recipe	Ready-to-use for utilities practitioners

References

1. **Hashemi, S. H., Karimi, A., & Tavana, M. (2015).** An integrated green supplier selection approach with analytic network process and **improved GRA**. *International Journal of Production Economics, 159*, 178–191. doi:10.1016/j.ijpe.2014.09.027. (IDEAS/RePEc)

2. **Wang, L., Yin, K., Cao, Y., & Li, X. (2019).** A new **IC-GRA** model and its application on China's seven-pilot carbon trading markets. *Int. J. Environ. Res. Public Health, 16*(1), 99. doi:10.3390/ijerph16010099. (PMC)

3. **Huang, Y., Shen, L., & Liu, H. (2019).** Grey relational analysis, principal component analysis and LSTM-based carbon emission forecasting. *Journal of Cleaner Production, 209*, 415–423. doi:10.1016/j.jclepro.2018.10.128. (UWF FLVC)

4. **Mahmoudi, A., et al. (2020).** Distinguishing coefficient driven sensitivity analysis of GRA. *Technological and Economic Development of Economy, 26*(4), 815–836. doi:10.3846/tede.2020.11890. (Vilnius Tech Journals)

5. **Esangbedo, M. O., & Wei, G. (2023).** Grey hybrid normalization with **period-based entropy weighting** and relational analysis for city rankings. *Scientific Reports, 13*, 13706. doi:10.1038/s41598-023-40954-4. (PMC)

6. **Rehman, A. U., et al. (2023).** An **entropy-based GRA** approach for dynamic manufacturing configurations. *Processes, 11*(11), 3151. doi:10.3390/pr11113151.

7. **Liu, H., et al. (2018).** Comprehensive evaluation of coal-fired power units using GRA and a hybrid **entropy-based** weighting method. *Energies, 11*(4), 215. doi:10.3390/e20040215. (PMC)

8. **Lu, N., et al. (2023).** GRA with cross-sequences and time-intervals. *Expert Systems with Applications*. (Elsevier). (ScienceDirect)

9. **Liu, D. K., et al. (2023).** Taguchi + GRA to optimize PV/T module parameters. *Sustainability, 15*(20), 15163. doi:10.3390/su152015163. (MDPI)

10. **Bircea, I. (2023).** Analysis of the financial performance of electricity companies (Bucharest Stock Exchange). *Applied Mathematics, Scientific and Operational Research, 7*(2), 33–44. doi:10.2478/amso-2023-0005. (Sciendo)