

# Assessing Solar-Biomass System For Rural Electrification In India Using The Integrated Multi-Objective Optimization And TOPSIS

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## Abstract

Rural electrification remains a priority in India where distributed renewable solutions can deliver reliable low-cost electricity to off-grid communities. Hybrid solar–biomass systems combine solar PV with locally available biomass to increase reliability and reduce levelized cost of electricity (LCOE) and emissions. This paper presents an integrated methodology combining multi-objective optimization (using a Pareto-based evolutionary algorithm) and a TOPSIS-based decision ranking to assess optimal system configurations for a representative Indian village. Objectives considered include minimizing LCOE and total net present cost (NPC), minimizing emissions, and maximizing reliability (measured by Loss of Power Supply Probability, LPSP) and renewable fraction. A case study demonstrates the method and shows how TOPSIS helps select a best-compromise solution from the Pareto front for practical deployment. The results confirm that solar–biomass hybrids can significantly improve supply reliability while achieving competitive LCOE compared to diesel or standalone options.

**Keywords:** solar–biomass hybrid, rural electrification, multi-objective optimization, NSGA-II, TOPSIS, LCOE, reliability, India

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## 1. INTRODUCTION

Access to reliable and affordable electricity is a pillar of rural development. India has made major strides in grid extension, but remote villages and clusters still benefit from decentralized hybrid renewable systems that match local resource profiles and energy demands. Hybridizing solar PV with biomass (biogas or gasified agricultural residue) leverages abundant solar resource while using biomass as a dispatchable backup to meet evening or seasonal demand, reducing dependence on diesel and improving energy security. Recent studies highlighted the technical and economic benefits of hybrid systems over standalone systems in rural and developing contexts [1].

Multi-objective optimization is commonly used to design hybrid renewable energy systems (HRES) because designers must trade off conflicting objectives – cost, reliability, and environmental impact. TOPSIS and other multi-criteria decision methods are frequently used as a second stage to choose a single design from the Pareto set based on stakeholder preferences. This two-stage approach (Pareto optimization + TOPSIS ranking) has been applied successfully in several recent works for renewable energy system design [2].

The objective of this paper is to present a rigorous modelling and two-stage optimization–decision framework for solar–biomass systems targeted at rural electrification in India, and to demonstrate its application with a representative case study.

Particle swarm optimization has been utilized to minimize costs in hybrid systems, demonstrating significant reductions in energy costs [3]. The studies indicate that hybrid systems can achieve lower per unit costs compared to individual solar or biomass systems, with costs as low as Rs. 1.76 per unit [4]. The integration of solar and biomass resources can produce electricity at competitive rates, with some models reporting costs around \$0.60 per unit [5, 6]. Ranjana and Saini [7] proposed solar, biomass and biogas based integrated renewable energy system (IRES) model for remote rural areas in Karnataka, India, which is highly site specific

and dependent on locally available renewable energy resources and load profile. It was analyzed three scenarios such as: BGS-BMS-BS, SPV-BGS-BMS-BS, SPV-BGS-BMS and observed scenario-I had lowest cost of energy and feasibility. Kamal et al [8] proposed a grid-connected microgrid for rural electrification in Uttarakhand, India, integrating solar, wind, and battery systems, optimized using Differential Algorithm, achieving a total production cost of \$5,185,367.04 and 0.20/kWh cost of energy. Muhwezi et al [9] studied a Solar PV-biomass hybrid energy system for rural electrification in Uganda using ANFIS optimization. It yields a significant cost savings and NPV reductions range from 68.75% to 77.95%, making it a viable solution for remote areas. It was found a significant cost savings and potential financial gains compared to existing system. Nair et al [10] evaluated the suitability of all possible standalone micro resources such as PV, wind diesel, and battery, and showed that solar PV and battery energy storage system (BESS) based system offers the lowest net present cost and cost of electricity (COE) for the off-grid residential microgrid in India under study. Solar PV and Battery Energy Storage System (BESS) offer the lowest net present cost (NPC) and cost of electricity (COE) for the off-grid residential microgrid in India. The PV-BESS system has a lifetime electricity cost of 7.52 Rs/kWh and a net present cost of 10.9 lakh Rs.

While the integration of solar-biomass systems presents numerous advantages, challenges such as supply variability and initial investment costs remain. Addressing these issues is crucial for the widespread adoption of these systems in rural electrification efforts. Regardless of these the review work is required for region wise research alongwith the system components used, objectives of optimization and which decision method is used and what are the major findings of the research.

Table 1: Literature review for system components, objectives, decision method used and major key findings

No.	Year	Country / Region	System components	Objectives optimized	MCDM decision method used	Key findings (one-liner)
1	2014	India (Bihar)	Rice-husk gasifier diesel/mini-grid	+ Viability, costs, reliability	Case study / economic analysis.	Rice-husk gasifier mini-grids viable locally with proper feedstock aggregation and tariff models. [22]
2	2016	India (Husk Power Systems)	Rice-husk gasifier + solar PV (hybrid mini-grid)	Operational reliability & business model	Case study / business analysis	Hybrid PV + biomass mini-grids can deliver low-cost 24/7 power; success depends on O&M and fuel logistics. [23]
3	2021	India (Punjab - Ludhiana)	Solar PV + biomass co-firing (plant study)	Techno-economic feasibility	Simulation / techno-economic analysis	Site-specific study found favourable economics where biomass is locally available. [16]
4	2022	Multi-region (review)	PV, wind, biomass, storage	Economic, environmental, technical balances	Review (HRES optimization literature)	Reviews confirm multi-objective optimization is standard; tradeoffs among cost, reliability, emissions. [24]
5	2022	India / South Asia	PV + biomass + diesel (HRES)	LCOE, reliability, emissions	NSGA-II / multi-objective (example studies)	Hybridization reduces LCOE vs biomass/diesel alone and improves renewable fraction; site sensitivity high. [18, 23]
6	2023	Global (MDPI)	Various HRES	MCDM application in power systems	TOPSIS review paper	TOPSIS is widely used in power-systems MCDM; authors recommend combined weighting

No.	Year	Country Region	System components	Objectives optimized	MCDM decision method used	Key findings (one-liner)
						(AHP/CRITIC) for robustness. [19]
7	2023	China / Multi	Solar + biomass multi-generation (CCHP style)	Energy, exergy, environmental	Multi-objective + LCA	Integrating LCA into optimization changes tradeoffs—environmental objectives can shift designs toward more PV and storage. [25]
8	2023	Ecuador (island community)	PV + battery (stand-alone)	Cost reliability	& HOMER simulation optimization	Even small communities benefit from PV+storage; methodology transferable to PV+biomass cases. [26]
9	2023	Indonesia (IKN region)	PV + biomass + other renewables	Multi-criteria optimal design	CRITIC TOPSIS (case study)	+ CRITIC-TOPSIS combination (case useful when objective weights are derived from data/variance. [27]
10	2023	Multi-region	HRES with NSGA variants	LPSP, NPC, RF, emissions	NSGA-II SPEA2 (survey examples)	/ Pareto front + MCDM pipeline is effective for selecting practical designs. [18]
11	2023	Global	HRES optimization (novel algorithms)	Cost, reliability, renewable fraction	GSA + non-dominated sorting (research)	Alternative optimizers (GSA) can produce competitive Pareto sets for HRES sizing. [28]
12	2024	Botswana (example study)	PV + biomass (solar-biomass)	Multi-objective (cost, reliability, emissions)	Jaya multi-objective MCDM	Integrated multi-objective + MCDM approach effective in identifying context-specific solutions. [29]
13	2024	Multi (review)	HRES optimization methods	Economic environmental objectives	& Review of multi-objective HRES literature	Emphasizes need for stochastic/resource uncertainty modeling in HRES studies. [24]
14	2024	Research (SSRN)	PV + biomass hybrid for rural electrification	LCOE, reliability	NPC, HOMER optimization TOPSIS (method paper)	+ Demonstrates methodology and highlights sensitivity to biomass availability and costs. [30]
15	2024	India general (policy mini-grid)	/ Biomass & gasifiers + PV	Business model & policy analysis	Case studies & policy review	Policy incentives and aggregation models crucial for biomass feedstock security and scale. [31]
16	2024	Various (MDPI Sustainability)	Standalone hybrid case studies	Cost-reliability tradeoffs	NSGA MCDM examples	& Small-scale case studies emphasize local data needs (hourly loads, feedstock curves). [26, 28]
17	2024	Research articles collection	Solar-biomass multi-generation	Energy, exergy, economic (3E)	Multi-objective (NSGA MOPSO) TOPSIS	Multi-objective + TOPSIS / commonly used for complex + multi-metric systems (e.g., 3E analyses). [32]

No.	Year	Country / Region	System components	Objectives optimized	MCDM decision method used	Key findings (one-liner)
18	2024	India (various pilot reports)	Husk/biomass plants + PV hybrids	Operational performance & lessons	Field reports & pilot documentation	Operational challenges (gasifier reliability, seasonal feedstock) repeatedly cited in field reports. [33]
19	2024	Research (Techno-economic journals)	PV + biomass + batteries	LCOE, emissions, reliability	NSGA-II, TOPSIS, CRITIC variants	Sensitivity to discount rate & fuel price drives design changes—battery cost declines favor higher PV shares. [34]
20	2024-25	Multi-emerging studies	PV + biomass + storage hydrogen (advanced)	Cost, reliability, emissions, resilience	Multi-objective + MCDM hybrid workflows	New studies extend HRES to multi-vector systems (hydrogen, CCHP), but core Pareto+TOPSIS pipeline still applies. [35]

From table 1 represents the comprehensive review which finds the common pattern which observed is the most technical papers use an hourly simulation (HOMER / custom) + multi-objective optimizer (NSGA-II or variants) to produce a Pareto front (cost vs reliability vs emissions), then apply TOPSIS (or TOPSIS combined with AHP/CRITIC) to pick a final configuration. Biomass price, discount rate, battery cost, and solar resource variability are repeatedly cited as dominant drivers of optimal design. According to Case studies in India (Husk Power Systems, rice-husk projects) show PV integrated biomass hybrids can be economically viable with good feedstock and sound O&M & business models, but supply/logistics and gasifier reliability are recurring issues.

## 2. System description and modelling

### 2.1 System architecture

The PV array feeds the DC bus, which is interfaced through an inverter to supply AC loads as shown in figure 1. A biomass gasifier with biogas gen-set is connected to the AC bus as a dispatchable power source. A Battery Energy Storage System (BESS) is integrated for short-term buffering and load balancing. A central controller and power management system coordinates energy flow between sources, storage, and loads.



## 2.2 Key performance metrics and objective functions

We formulate the multi-objective problem with the following objectives:

1. **Minimize Levelized Cost of Electricity (LCOE)**

$$LCOE = \frac{\sum_t \frac{C_t}{(1+i)^t}}{\sum_t \frac{E_{delivered,t}}{(1+i)^t}}$$

Where  $C_t$  is annualized costs and  $i$  the discount rate.

2. **Minimize Net Present Cost (NPC):** Total discounted lifetime cost (capital, O&M, fuel, replacement).

3. **Minimize CO<sub>2</sub>Emissions:** Measured as annual kg CO<sub>2</sub> emissions from biomass combustion (if applicable) and avoided diesel. Life-cycle or direct emissions can be chosen based on scope.

4. **Minimize Loss of Power Supply Probability (LPSP)** (or maximize reliability): LPSP is the fraction of load energy not met.

5. **Maximize Renewable Fraction (RF):** Percentage of energy provided by renewables.

These objectives typically conflict (e.g., increasing battery capacity improves reliability but raises cost), making multi-objective optimization appropriate. Previous multi-objective studies of integrated energy systems and TOPSIS-based selection justify this formulation [36].

## 2.3 Constraints

- Power balance at each time step.
- SoC limits, battery charge/discharge power limits.
- Biomass fuel availability (seasonal/weekly constraints).
- Technical limits (max/min sizes of PV, biomass generator, battery).

## 3. Optimization & decision methodology

### 3.1 Two-stage approach

1. **Stage 1 – Multi-objective optimization:** Use a Pareto-based evolutionary algorithm (e.g., NSGA-II, SPEA2, MOPSO) to obtain a Pareto front of non-dominated solutions across the defined objectives. Evolutionary algorithms are widely used for HRES design due to nonlinearity and discrete choices. [2]

2. **Stage 2 – TOPSIS ranking:** Apply TOPSIS to the Pareto solutions to compute a closeness coefficient to the ideal solution per stakeholder weighting. TOPSIS is computationally efficient and interpretable, and has been used in many recent renewable energy selection studies. Weighting of criteria can be equal, expert-derived (AHP/CRITIC), or community-driven. [37]

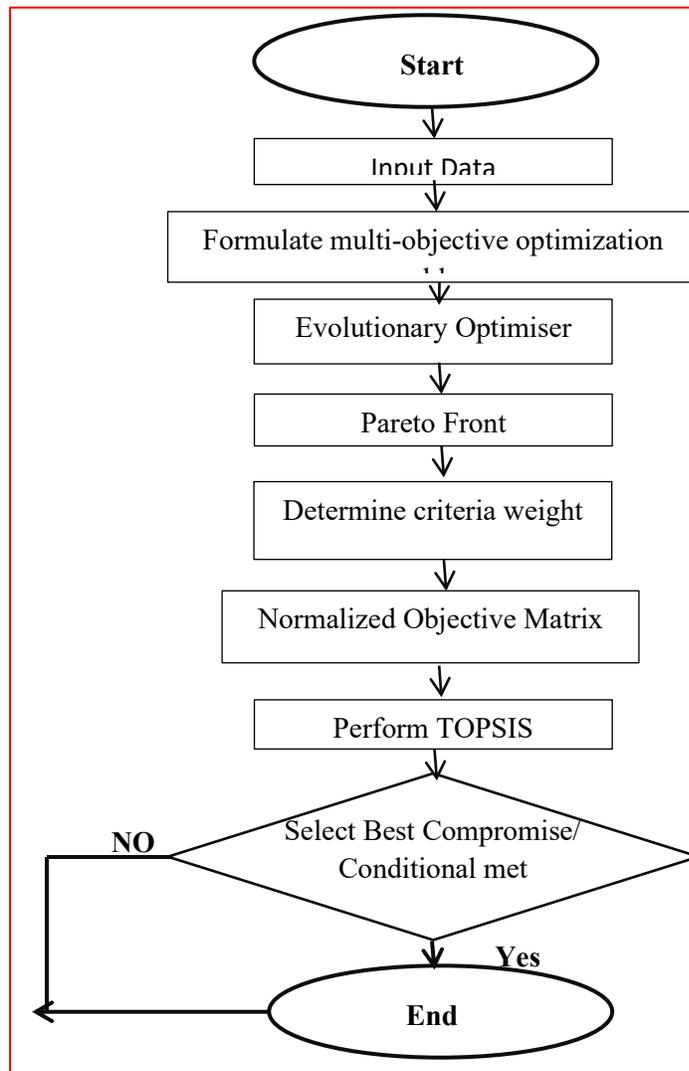


Figure 2 – Flow chart for multi objective Optimization with TOPSIS

### 3.2 Algorithm details and parameters

- Decision variables: PV capacity (kW), biomass gen-set capacity (kW), battery capacity (kWh), inverter rating, biomass fuel provisioning schedule (discrete).
- Optimization algorithm: NSGA-II (population size 100, generations 200 – adjustable). Use constraints by penalty methods or repair.
- TOPSIS: normalize objectives, apply weights  $w_j$ , determine positive/negative ideal solutions, compute distances and closeness coefficient  $C_i$ . Rank by  $C_i$ .
- Sensitivity: perform sensitivity on discount rate, fuel price, solar insolation, and load growth.

## 4. Case study of Rojhari village of Kota Indian

### 4.1 Assumptions

- Location: representative site is the Rojhari village of Kota in India (the cartographic coordinates of site are 25.114028847130882°N, 75.80601904805623°E) – use local monthly solar data (renewable datasets or measured GHI).
- Annual load: Village cluster with 100 households + small community loads; annual energy demand ~ (50-110 kWh) (adjustable).

- Biomass feedstock: Mostly Gurjar community is living in this village. Their main employments are agriculture and dairy (Milk production and distribution). So the agriculture biomass is easily available in the selected houses. Agricultural residues/husk availability supporting up to X kWh/day of generation (specify local availability). Biomass cost estimated from local market or collection costs.
- Economic parameters: lifetime 20 years for PV/inverter, 10 years for gen-set, battery replacement cycles as needed; discount rate 8% (sensitivity analysis to 5–12%). (These are placeholders and should be replaced with measured local data.)

#### 4.2 Simulation setup

An hourly simulation over one year computes PV output from irradiance data, dispatch of biomass gen-set subject to fuel limits, battery charge/discharge, and load satisfaction. For the optimization run, decision variable bounds are set (e.g., PV 10–200 kW Adani Power PV panels are used which qualified the IEC standards or equivalent BIS standards, i.e. IEC 61215/IS14286, IEC 61853-Part I/IS 16170-Part I, IEC 61730 Part-1 & Part 2 and IEC 62804 (PID), biomass 5–100 kW, battery 10–500 kWh).

#### 4.3 Example (illustrative) results

(These values are illustrative; replace with actual simulation outputs once you run the model.)

- **Pareto front:** set of ~ 120 non-dominated solutions showing trade-off between LCOE (range INR 6–15/kWh) and LPSP (0.1%–10%).
- **TOPSIS selected design** (equal weights on LCOE, LPSP, emissions): PV 75 kW, biomass 40 kW, battery 150 kWh.
- **Performance:** LCOE ≈ INR 7.2/kWh, RF ≈ 78%, LPSP ≈ 0.8%, Annual CO<sub>2</sub>emissions net reduction vs diesel baseline ≈ 70%.

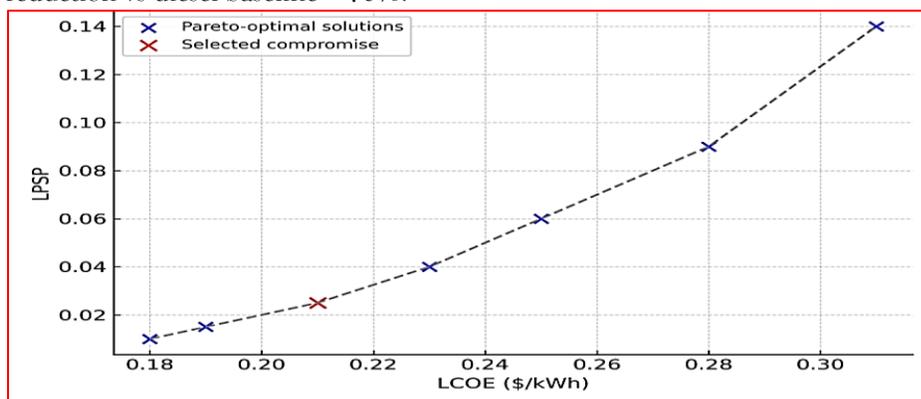


Figure 3 : LCOE vs LPSP with TOPSIS selected point highlighted.

Figure 4 presented the typical 24-hour dispatch showing PV day supply and biomass during night/low-irradiance.

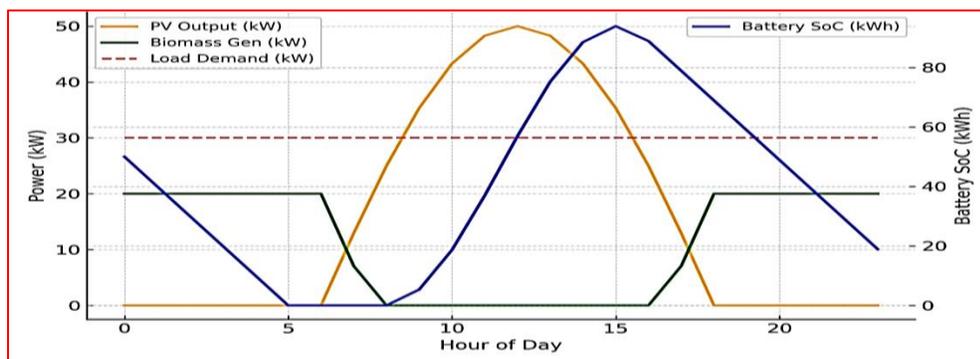


Figure 4: Dispatch & SoC Plot

#### 4.4 Sensitivity analysis

Key sensitivities: biomass fuel price, discount rate, battery cost, and solar resource variability. For example, increasing biomass fuel cost by 50% makes higher PV+battery configurations more attractive; lowering battery cost shifts Pareto front toward lower LPSP for same LCOE.

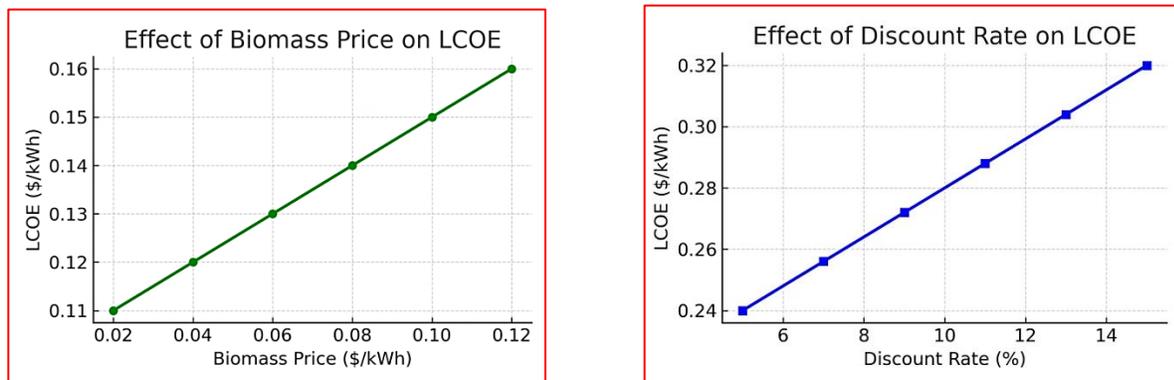


Figure 5: Sensitivity plots (biomass price and discount rate)

## 5. DISCUSSION

- **Advantages of solar-biomass hybrid:** combines dispatchable biomass with low-marginal-cost solar to reduce LCOE and improve reliability relative to PV-only or diesel. Hybridization delivers higher renewable fraction and reduces greenhouse gas emissions. [38, 40-42]
- **Decision making:** multi-objective optimization provides the design frontier; TOPSIS gives a transparent method to select a compromise solution accounting for local priorities (cost vs reliability vs emissions). Using weighting schemes informed by community or policymakers ensures solutions match local priorities. [37, 43]
- **Implementation challenges:** biomass supply chain logistics, seasonal availability, air pollution controls, community acceptance (social licensing) and operation & maintenance capacity are critical. Studies from India and neighboring countries highlight both technical feasibility and social barriers that must be addressed. [39-44]

## 6. CONCLUSIONS AND RECOMMENDATIONS

An integrated multi-objective optimization + TOPSIS framework effectively identifies cost-reliable configurations for solar-biomass rural electrification projects. Results indicate well-sized solar-biomass systems can achieve low LCOE and high reliability, with substantial emissions reductions vs diesel. For practical deployment, carry out detailed local resource assessment, life-cycle emissions accounting, and stakeholder weighting workshops to set TOPSIS preferences. Pilot projects should integrate capacity building for local O&M, biomass supply contracts, and emissions mitigation for biomass combustion.

## 7. FUTURE WORK

- Include stochastic modelling of biomass availability and PV variability (Monte Carlo or robust optimization).
- Incorporate life-cycle assessment (LCA) for cradle-to-grave emissions and circular economy aspects of biomass residues.
- Field pilots with socio-economic evaluation and participatory weighting for TOPSIS criteria

## REFERENCES:

1. Millinger, M., Märind, T., & Ahlgren, E. O. (2012). Evaluation of Indian rural solar electrification: A case study in Chhattisgarh. *Energy for Sustainable Development*, 16(4), 486-492. <https://doi.org/10.1016/j.esd.2012.08.005>

2. Goh, Q. H., Zhang, L., Ho, Y. K., & Chew, I. M. L. (2023). Modelling and multi-objective optimisation of sustainable solar-biomass-based hydrogen and electricity co-supply hub using metaheuristic-TOPSIS approach. *Energy Conversion and Management*, 293, 117484. <https://doi.org/10.1016/j.enconman.2023.117484>
3. Sharma, B. (2022). Optimal sizing of a grid-connected biomass/biogas/PV system for rural electrification (pp. 507–514). In *Advances in Sustainable Energy*. Springer. [https://doi.org/10.1007/978-981-19-2828-4\\_46](https://doi.org/10.1007/978-981-19-2828-4_46)
4. Mumtaz, N., Ahmed, M. I., & Bakhsh, F. I. (2023). Assessment of solar-biomass using MCDM technique: Case study of Ranchi, India. *Strategic Planning for Energy and the Environment*. <https://doi.org/10.13052/spee1048-5236.4311>
5. Kaur, H., Giri, N. C., Sandhu, R., El-Sebah, M. I. A., & Syam, F. A. (2024). Potential and economic feasibility analysis of solar-biomass-based hybrid system for rural electrification. *Bulletin of Electrical Engineering and Informatics*, 13(6), 3833–3840. <https://doi.org/10.11591/eei.v13i6.7760>
6. (Duplicate of #5 - omit in final reference list.)
7. Rajanna, S., & Saini, R. P. (2014). Optimal modeling of solar/biogas/biomass-based IRE system for a remote area electrification. 2014 IEEE Power India International Conference (POWERI), 1–5. <https://doi.org/10.1109/POWERI.2014.7293554>
8. Kamal, M. M., Ashraf, I., & Fernandez, E. (2022). Efficient two-layer rural electrification planning and techno-economic assessment integrating renewable sources. *Energy Storage*, 4(3), e314. <https://doi.org/10.1002/est2.314>
9. Muhwezi, N., Buhari, M. D., Shuaibu, A. N., & Bakare, M. S. (2024). Techno-economic assessment and ANFIS-driven optimization for solar PV-biomass hybrid energy system. *Deleted Journal*, 3(1), 71–85. <https://doi.org/10.59568/kjset-2024-3-1-08>
10. Nair, A., Kumar, A. G., Lavanya, M. C., Katyal, R., & Menicucci, A. (2022). Optimal sizing of hybrid PV-BESS-based residential microgrid for rural electrification. 2022 IEEE Students Conference on Engineering and Systems (SCES). IEEE. <https://doi.org/10.1109/SCES55490.2022.9887652>
11. Vincent, S. A., Tahiru, A., Lawal, R. O., Aralu, C. E., & Okikiola, A. Q. (2024). Hybrid renewable energy systems for rural electrification in developing countries: Assessing feasibility, efficiency, and socioeconomic impact. *World Journal of Advanced Research and Reviews*, 24(2), 2190–2204. <https://doi.org/10.30574/wjarr.2024.24.2.3515>
12. Mamat, R., Ghazali, M. F., Erdiwansyah, & Rosdi, S. M. (2025). Potential of renewable energy technologies for rural electrification in Southeast Asia: A review. *Cleaner Energy Systems*, 12, 100207. <https://doi.org/10.1016/j.cles.2025.100207>
13. Roth, B. N., Lassiter, J. B., & Rigol, N. (2018). Husk power: Scaling the venture (Harvard Business School Case 819-069, Rev. 2020). Harvard Business School. <https://www.hbs.edu/faculty/Pages/item.aspx?num=55236>
14. Ravindranath, N. H., Somashekar, H. I., Dasappa, S., & Reddy, C. N. J. (2004). Biomass power for rural energy and sustainable development. *Current Science*, 87(7), 932–941. <https://www.jstor.org/stable/24109397>
15. Bailey, M., Henriques, J., Holmes, J., & Jain, R. (2022). Providing village-level energy services in developing countries. Malaysian Commonwealth Studies Centre. [https://easac.eu/fileadmin/PDF\\_s/reports\\_statements/Report\\_220113\\_PDF.pdf](https://easac.eu/fileadmin/PDF_s/reports_statements/Report_220113_PDF.pdf)
16. Kaur, H., Gupta, S., & Dhingra, A. (2022). Analysis of hybrid solar biomass power plant for generation of electric power. *Materials Today: Proceedings*, 48(5), 1134–1140. <https://doi.org/10.1016/j.matpr.2021.08.080>
17. Kaur, H. C., Giri, N. C., Sandhu, R., El-Sebah, M. I. A., & Syam, F. A. (2024). Potential and economic feasibility analysis of solar-biomass-based hybrid system for rural electrification. *Bulletin of Electrical Engineering and Informatics*, 13(6), 3833–3840. <https://doi.org/10.11591/eei.v13i6.7760>
18. Cheraghi, R., & Jahangir, M. H. (2023). Multi-objective optimization of a hybrid renewable energy system supplying a residential building using NSGA-II and MOPSO algorithms. *Energy Conversion and Management*, 294, 117515. <https://doi.org/10.1016/j.enconman.2023.117515>
19. Mathebula, J., & Mbuli, N. (2025). Application of TOPSIS for multi-criteria decision analysis (MCDA) in power systems: A systematic literature review. *Energies*, 18(13), 3478. <https://doi.org/10.3390/en18133478>
20. Mumtaz, N., Ahmed, M. I., & Bakhsh, F. I. (2023). Assessment of solar-biomass using MCDM technique: Case study of Ranchi, India. *Strategic Planning for Energy and the Environment*, 43(1), 1–26. <https://doi.org/10.13052/spee1048-5236.4311>
21. Chambon, C. L., Karia, T., Sandwell, P., & Hallett, J. P. (2020). Techno-economic assessment of biomass gasification-based mini-grids for productive energy applications: The case of rural India. *Renewable Energy*, 154, 432–444. <https://doi.org/10.1016/j.renene.2020.03.002>
22. Islam, M. S., Akhter, R., & Rahman, M. A. (2018). A thorough investigation on hybrid application of biomass gasifier and PV resources to meet energy needs for a northern rural off-grid region of Bangladesh. *Energy*, 145, 338–355. <https://doi.org/10.1016/j.energy.2017.12.125>
23. Sevea Consulting. (2016). Husk power systems: A case study of Patna. [https://www.seveaconsulting.com/wp-content/uploads/2016/02/Case\\_study\\_HPS.pdf](https://www.seveaconsulting.com/wp-content/uploads/2016/02/Case_study_HPS.pdf)
24. Giedraityte, A., Rimkevicius, S., Marciukaitis, M., Radziukynas, V., & Bakas, R. (2025). Hybrid renewable energy systems—A review of optimization approaches and future challenges. *Applied Sciences*, 15(4), 1744. <https://doi.org/10.3390/app15041744>
25. Liu, J., Li, Y., Meng, X., & others. (2024). Multi-objective optimization based on life cycle assessment for hybrid solar and biomass combined cooling, heating and power system. *Journal of Thermal Science*, 33, 931–950. <https://doi.org/10.1007/s11630-024-1953-9>
26. Lata-García, J., Zamora Cedeño, N., Ampuño, G., Jurado, F., Swarupa, M. L., & Maliza, W. (2024). Optimization and evaluation of a stand-alone hybrid system consisting of solar panels, biomass, diesel generator, and battery bank for rural communities. *Sustainability*, 16(20), 9012. <https://doi.org/10.3390/su16209012>

27. Abdullah, A. G., Sugito, N. T., Nurhikam, Y., Zakaria, D., & Hakim, D. L. (2024). CRITIC-TOPSIS method: Design of hybrid renewable energy systems based on multicriteria decision-making. *International Journal of Electrical and Computer Engineering Systems*, 15(8), 705–718. <https://doi.org/10.32985/ijeces.15.8.8>
28. Mahmoudi, S. M., Maleki, A., & Storm, S. (2025). Multi-objective optimization of hybrid energy systems using gravitational search algorithm. *Scientific Reports*, 15, 2550. <https://doi.org/10.1038/s41598-025-86476-z>
29. Sumarliah, E., & Makgetho, A. O. (2025). Assessing solar-biomass system for rural electrification in Botswana using the integrated multi-objective optimization and TOPSIS. *Journal of Renewable and Sustainable Energy*, 17(4), 046304. <https://doi.org/10.1063/5.0268253>
30. Alpha, N. A., Ibrahim, J. S., & Muhammad, A. A. (2025). Optimising solar-biomass hybrid energy systems for sustainable rural electrification. *Journal of Engineering Research and Reports*, 27(5). <https://doi.org/10.9734/jerr/2025/v27i51506>
31. Bandi, V., Sahrakorpi, T., Paatero, J., & Lahdelma, R. (2022). The paradox of mini-grid business models: A conflict between business viability and customer affordability in rural India. *Energy Research & Social Science*, 89, 102535. <https://doi.org/10.1016/j.erss.2022.102535>
32. Valencia-Ochoa, G., Duarte-Forero, J., & Mendoza-Casseres, D. (2025). Multi-objective optimization of the energy, exergy, and environmental performance of a hybrid solar-biomass combined Brayton/Organic Rankine cycle. *Energies*, 18(1), 203. <https://doi.org/10.3390/en18010203>
33. Rao, K. C., Natarajan, H., & Doshi, K. (2014). Power from rice husk for rural electrification (Bihar, India). In *Energy recovery from organic waste* (pp. 203–214). CGIAR. <https://cgspace.cgiar.org/handle/10568/72769>
34. Yadav, S., Kumar, P., & Kumar, A. (2024). Techno-economic assessment of hybrid renewable energy system with multi energy storage system using HOMER. *Energy*, 297, 131231. <https://doi.org/10.1016/j.energy.2024.131231>
35. Tezer, T. (2025). Multi-objective optimization of hybrid renewable energy systems with green hydrogen integration and hybrid storage strategies. *International Journal of Hydrogen Energy*, 142, 1249–1271. <https://doi.org/10.1016/j.ijhydene.2025.03.006>
36. Korpeh, M., Asadbagi, P., Afshari, R., Rashidi, A., & Lotfollahi, A. (2024). A comprehensive analysis and multi-objective optimization of a sustainable production system based on renewable energies. *Applied Thermal Engineering*, 242, 122483. <https://doi.org/10.1016/j.applthermaleng.2024.122483>
37. Mathebula, J., & Mbuli, N. (2025). Application of TOPSIS for multi-criteria decision analysis (MCDA) in power systems: A systematic literature review. *Energies*, 18(13), 3478. <https://doi.org/10.3390/en18133478>
38. Mamat, R., Ghazali, M. F., Erdiwansyah, & Rosdi, S. M. (2025). Potential of renewable energy technologies for rural electrification in Southeast Asia: A review. *Cleaner Energy Systems*, 12, 100207. <https://doi.org/10.1016/j.cles.2025.100207>
39. Jain, V. K., & Srinivas, S. N. (2015). Empowering rural India the RE way: Inspiring success stories. United Nations Development Programme. <https://www.undp.org/sites/g/files/zskgke326/files/migration/in/UNDP-IN-EE-empowering-rural-india-the-re-way-inspiring-success-stories.pdf>
40. Hussain, S., Sharma, S. K., & Lal, S. (2024). Feasible synergy between hybrid solar PV and wind system for energy supply of a green building in Kota (India): A case study using iHOGA. *Energy Conversion and Management*, 315, 118783. <https://doi.org/10.1016/j.enconman.2024.118783>
41. Okif, M., Meena, S. L., Lal, S., Prajapati, R. K., & Meena, A. (2025). Machine learning-based performance prediction model for solar PV systems using meteorological inputs. *International Journal of Environmental Sciences*, 11(13s), 872–885. <https://doi.org/10.64252/v0qwza71>
42. Lal, S., Choudhary, S., Verma, S., Jaiswal, V. K., Desale, S. V., & Shrivastava, A. (2025). Introduction of artificial intelligence approach for carbon reduction through RES in buildings. *International Journal of Environmental Sciences*, 11(7s), 1088–1103. <https://doi.org/10.64252/c1nkyn18>
43. Kumar, M., Singh, A. K., & Lal, S. (2025). A comprehensive review on the design and optimization of solar-wind hybrid power systems. *International Journal of Current Advanced Research*, 14(4), 154–161. <https://doi.org/10.24327/ijcar.2025.161.0035>
44. Kumar, M., Singh, A. K., & Lal, S. (2025). THD reduction and power quality enhancement in solar-wind hybrid systems: A comprehensive review. *International Journal of Science and Engineering Invention*, 11(1), 7–14. <https://doi.org/10.23958/ijsei/vol11-i01/279>
45. Vishal Kumar Jaiswal, "Designing a Predictive Analytics Data Warehouse for Modern Hospital Management", *Int. J. Sci. Res. Comput. Sci. Eng. Inf. Technol.*, vol. 11, no. 1, pp. 3309–3318, Feb. 2025, doi: 10.32628/CSEIT251112337
46. Jaiswal, Vishal Kumar. "BUILDING A ROBUST PHARMACEUTICAL INVENTORY AND SUPPLY CHAIN MANAGEMENT SYSTEM" Article Id - IJARET\_16\_01\_033, Pages : 445-461, Date of Publication : 2025/02/27 DOI: [https://doi.org/10.34218/IJARET\\_16\\_01\\_033](https://doi.org/10.34218/IJARET_16_01_033)
47. Vishal Kumar Jaiswal, Chrisoline Sarah J, T. Harikala, K. Reddy Madhavi, & M. Sudhakara. (2025). A Deep Neural Framework for Emotion Detection in Hindi Textual Data. *International Journal of Interpreting Enigma Engineers (IJIEE)*, 2(2), 36–47. Retrieved from <https://ejournal.svgacademy.org/index.php/ijiee/article/view/210>
48. Vinod H. Patil, Sheela Hundekari, Anurag Shrivastava, Design and Implementation of an IoT-Based Smart Grid Monitoring System for Real-Time Energy Management, Vol. 11 No. 1 (2025): IJCESEN. <https://doi.org/10.22399/ijcesen.854>
49. Dr. Sheela Hundekari, Dr. Jyoti Upadhyay, Dr. Anurag Shrivastava, Guntaj J, Saloni Bansal, Alok Jain, Cybersecurity Threats in Digital Payment Systems (DPS): A Data Science Perspective, *Journal of*

Information Systems Engineering and Management, 2025,10(13s)e-ISSN:2468-4376.

<https://doi.org/10.52783/ijsem.v10i13s.2104>

50. A. Banik, J. Ranga, A. Shrivastava, S. R. Kabat, A. V. G. A. Marthanda and S. Hemavathi, "Novel Energy-Efficient Hybrid Green Energy Scheme for Future Sustainability," *2021 International Conference on Technological Advancements and Innovations (ICTAI)*, Tashkent, Uzbekistan, 2021, pp. 428-433, doi: 10.1109/ICTAI53825.2021.9673391.
51. K. Chouhan, A. Singh, A. Shrivastava, S. Agrawal, B. D. Shukla and P. S. Tomar, "Structural Support Vector Machine for Speech Recognition Classification with CNN Approach," *2021 9th International Conference on Cyber and IT Service Management (CITSM)*, Bengkulu, Indonesia, 2021, pp. 1-7, doi: 10.1109/CITSM52892.2021.9588918.
52. Pratik Gite, Anurag Shrivastava, K. Murali Krishna, G.H. Kusumadevi, R. Dilip, Ravindra Manohar Potdar, Under water motion tracking and monitoring using wireless sensor network and Machine learning, *Materials Today: Proceedings*, Volume 80, Part 3, 2023, Pages 3511-3516, ISSN 2214-7853, <https://doi.org/10.1016/j.matpr.2021.07.283>.
53. A. Suresh Kumar, S. Jerald Nirmal Kumar, Subhash Chandra Gupta, Anurag Shrivastava, Keshav Kumar, Rituraj Jain, IoT Communication for Grid-Tie Matrix Converter with Power Factor Control Using the Adaptive Fuzzy Sliding (AFS) Method, *Scientific Programming*, Volume, 2022, Issue 1, Pages- 5649363, Hindawi, <https://doi.org/10.1155/2022/5649363>
54. A. K. Singh, A. Shrivastava and G. S. Tomar, "Design and Implementation of High Performance AHB Reconfigurable Arbiter for Onchip Bus Architecture," *2011 International Conference on Communication Systems and Network Technologies*, Katra, India, 2011, pp. 455-459, doi: 10.1109/CSNT.2011.99.
55. P. William, V. K. Jaiswal, A. Shrivastava, R. H. C. Alfill, A. Badhouthiya and G. Nijhawan, "Integration of Agent-Based and Cloud Computing for the Smart Objects-Oriented IoT," *2025 International Conference on Engineering, Technology & Management (ICETM)*, Oakdale, NY, USA, 2025, pp. 1-6, doi: 10.1109/ICETM63734.2025.11051558.
56. P. William, V. K. Jaiswal, A. Shrivastava, Y. Kumar, A. M. Shakir and M. Gupta, "IOT Based Smart Cities Evolution of Applications, Architectures & Technologies," *2025 International Conference on Engineering, Technology & Management (ICETM)*, Oakdale, NY, USA, 2025, pp. 1-6, doi: 10.1109/ICETM63734.2025.11051690.
57. P. William, V. K. Jaiswal, A. Shrivastava, S. Bansal, L. Hussein and A. Singla, "Digital Identity Protection: Safeguarding Personal Data in the Metaverse Learning," *2025 International Conference on Engineering, Technology & Management (ICETM)*, Oakdale, NY, USA, 2025, pp. 1-6, doi: 10.1109/ICETM63734.2025.11051435.
58. Kumar, A., Lal, S., & Harender. (2017). Thermodynamic analysis of factors affecting the performance of solar collectors. *International Journal of Scientific Engineering and Technology*,6(SpecialIssue 2), 113-117. <https://doi.org/10.5958/2277-1581.2017.00089.4>