Assessment of Clean Energy Transition Potential in Major Power-Producing States of India Using Multi-Criteria Decision Analysis

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Abstract: India has an ambitious target to promote clean energy penetration, but as of 2021, the electricity mix of India is dominated by coal to about 71%. Therefore, analyzing the clean energy potential and the ability of the individual states to entrench energy transition in the upcoming years will be supportive for policymakers. This study is propounded to assess the clean energy transition potential with a focused analysis on seven major power-producing states of India. These states include Maharashtra, Gujarat, Tamil Nadu, Uttar Pradesh, Karnataka, Madhya Pradesh, and Andhra Pradesh. The clean energy transition potential assessment is performed by utilizing multi-criteria decision analysis methodologies such as the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and Multi-Objective Optimization Method by Ratio Analysis (MOORA). Further, the analysis is performed against four major criteria that include high carbon energy resource dependency, low carbon energy resource dependency, clean energy potential, and policy support. Altogether, the assessment criteria include four primary level criteria and fourteen secondary level parameters. In order to reflect the significance of each parameter and criterion to the characteristics of clean energy transition potential, appropriate weightage is provided using the Fuzzy Analytic Hierarchy Process (AHP). The results indicate that Gujarat has the highest clean energy transition potential in both the multi-criteria decision analysis methods. On the other hand, Uttar Pradesh exhibited the least performance, and a complete energy transition to clean energy resources is less likely in this state. The rest of the states obtained intermediate ranking, and a comparative analysis between the two methods was also accomplished. This study suggests that India should focus on the clean energy policy with vigorous efforts on top-performing states which will effectively accelerate the power sector decarbonization.

Keywords: multi-criteria decision analysis; TOPSIS; MOORA; Fuzzy AHP; clean energy transition potential; India

1. Introduction

The energy sector dependency should be revamped from fossil fuel resources to clean energy resources, and optimized energy configuration is required to achieve energy sustainability [1]. A specific focus on the power sector is desideratum since it provides a firm foundation to decarbonize the energy sector completely. Given the population growth, urbanization, and other development factors that are favored in the upcoming years, the utilization of electricity would increase [2,3]. Thus, policies and investments should be focused on decarbonizing the power sector in the upcoming years. On investigating the electricity consumption of various countries across the world, it can be observed that China, the United States, and India are the countries having the highest power consumption in the world. The amount of electricity consumed by the top 10 countries is presented in Figure 1.
As of 2018, India is the third-largest greenhouse gas (GHG) emitter accounting for about 3346.63 MtCO2 equivalents [5]. Besides, India’s future trajectory has the potential to emit more emissions in the upcoming years such that the increase in emissions can surpass the United States by about 2035 [6]. This can be attributed to an increase in per capita emissions and access to energy. Therefore, decarbonizing the various sectors of India would contribute to reducing global emissions significantly. India witnessed a surge in electricity generation in the past decade, and in 2020, the electricity generated in India was about 1342 TWh which is 62.8% higher when compared to 2010 [7]. The reason for the increase in electricity generation is linked to population factors, increased electrification, and urbanization [8]. Figure 2 shows the electricity mix of India from 2010 to 2020. In 2020, it can be observed that India’s electricity primarily depends on coal which constitutes around 71%. Among the renewables, hydropower contributes the highest (12.2%), while solar and wind energy constitutes 4.4% and 4.5%, respectively.

Figure 1. Top 10 highest electricity consuming countries. Data source [4].

Figure 2. Indian electricity mix from 2010 to 2020. Data source: [7].
For achieving decarbonization and the Paris agreement, focused and strategical investment is of the utmost importance, and most of these investments are required in the developing countries [9]. Further, deep decarbonization is an extremely convoluted and systematic process that requires blended contributions from policies, technologies, people, companies, and markets [10–13]. The power sector is the most significant sector contributing to India’s total GHG emissions [14], and decarbonizing the power sector is closely interlinked with digitalization and decentralization [15]. The major challenges accompanying the decarbonization of the energy sector rely on energy security, environmental sustainability, social factors, and economic stability [16]. Further, the studies suggest that a global carbon tax is an effective policy instrument that can accelerate the decarbonization process [16]. As a contribution to decarbonizing the Indian power sector, this study is proposed to assess the clean energy transition potential of the country by selectively focusing on major power-producing states. By doing so, a bigger picture on a decentralized state-wise decarbonization vision can be accomplished. On the other hand, the clean energy transition potential is the key to decarbonization, and the analysis performed will be of crucial importance for the policymakers and energy companies to tap the untapped clean energy potential.

The section-wise content description is as follows. Section 2 presents the literature review, knowledge gap, and contributions of this study. Section 3 deals with the selection of major power-producing states of India. Section 4 elaborates the methodology in terms of the assessment criteria description as well as utilized MCDA methods’ elucidation. Section 5 presents the results of obtained weightage through Fuzzy AHP, MCDA results of TOPSIS, and MOORA, as well as a comparative analysis. Section 6 presents the policy implications, while Section 7 summarizes and concludes this study.

2. Literature Review

Pradhan et al. utilized the Computable General Equilibrium (CGE) model to investigate coal tax and renewable energy technologies for an effective energy transition [17]. The study highlighted that high carbon pricing can be conducive to an energy transition but has the potential to degrade the income distribution. Besides, the endogenous development in renewable energy technologies can bolster economic as well as income equality. A study argues that engaging with the energy sector workforce and citizens, implementing low-cost financing and carbon pricing, and emphasizing co-benefits in development are the key to achieving a net-zero carbon energy sector in India [18]. Azad and Chakraborty proposed the Energy Policy with Equity for India to accelerate the energy transition [19]. This policy mobilizes the taxed money to invest in renewables and provide free energy to the household up to a certain limit. To implement such policy efforts, the authors put forward that the required tax rate would be $60.4 per metric ton of carbon dioxide, while the free entailment of fuel and electricity contributes around 2268 kWh per household per annum.

Godil et al. used the Quantile Autoregressive Distributed Lag (QARDL) method to analyze the factors influencing energy utilization in India [20]. The results suggest that globalization and financial performance have a positive influence on energy utilization, whereas R&D and institutional quality have a negative influence on energy utilization. On analyzing the clean energy consumption pattern of urban households in India, it is observed that those households with low income and a lack of education are the significant influencing factor for the reliance on dirty fuels [21]. Therefore, the study suggests that framing the policies inclusive to enhance education and income will assist in the clean energy transition.

Madurai Elavarasan et al. reviewed the development of renewable energy, challenges, and policies in Indian states [22]. Saraswat and Digalwar evaluated the energy alternatives such as thermal, gas, nuclear, solar, wind, biomass, and hydro energy for sustainable development of the Indian energy sector by using an integrated Shannon’s entropy fuzzy multi-criteria decision approach [23]. The energy alternatives were assessed with technical, economic, environmental, social, political, and flexible criteria. The results demonstrated
that solar energy is the best energy alternative that can promote energy sustainability in India followed by wind and hydro energy resources. In another study, the same group of scholars performed an empirical investigation and validation of indicators for investigating the energy sources in India through the sustainability importance index [24]. A study analyzed the potential of solar and wind energy resources in India [25]. The results highlight that the estimated availability of solar energy falls within the Levelized Cost of Energy (LCOE) range of 51.6 $/MWh to 89 $/MWh. Concerning wind energy resources, a total of 3102 GW of wind capacity is estimated that can be below 115 $/MWh of LCOE. Pathak et al. analyzed the barriers to the development of renewable energy technologies in India through an integrated modified Delphi and AHP methodology [26]. The results show that political barriers tend to be the major barrier to renewable energy penetration in India.

To perform a robust analysis to assess the clean energy transition potential quantitatively, several criteria and parameters need to be selected as well as an appropriate methodology being pivotal. A multi-criteria decision analysis (MCDA) methodology is more suitable because the method can handle ambiguity, a multitude of perspectives, and conflicting criteria, and it produces an aggregated result based on which solid conclusions can be obtained [27]. Some unique advantages that MCDA offers to policymakers include (i) building an evidence-based system to capture the economic, environmental, social, technological, and other metrics via quantitative as well as qualitative attributes; (ii) offering a flexible view since the decision can be obtained in a finite set of objectives from a large set of actors; (iii) analyzing the synergic and trade-off effect induced on the objective by numerous factors [28].

The MCDA technique is utilized in a number of studies and applications such as the evaluation of challenges in reliable solar panel selection [29], measurement technique selection for particulate matter emission [30], sustainable material selection for construction projects [31], utility-scale solar photovoltaic siting with social considerations [32], performance assessment of alternative jet fuels [33], sustainability evaluation of the energy sector [34], analysis of waste-to-energy management strategies [35], sustainability analysis of the second generation of biofuels [36], and assessment of energy storage systems for grid applications [37]. Further, studies focusing on a country or location-specific assessment were also found to utilize MCDA methodology. Some of the examples include sustainable energy consumption evaluation in Europe [38], sustainability assessment of alternatives for waste plastics in Norway [39], optimal location selection for solar energy plants in Indonesia [40], investigation of the potential of renewable energy sources for electricity generation in Serbia [41], and assessment of the success factors for the sustainable energy sector in China for prioritization [42].

In the studies using MCDA, the widely employed methods include the Best-Worst Method (BWM) [43–45], Analytic Hierarchy Process (AHP) [46–48], Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE)—I and II [49–52], VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) [53–55], Elimination and Choice Translating Reality (ELECTRE) [56,57], Decision making trial and evaluation laboratory (DEMATEL) [58–60], and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [61–63]. Further, the studies that deal with qualitative attributes utilize fuzzified MCDA approaches such as Fuzzy AHP [64,65], Fuzzy TOPSIS [66,67], and many others. All these MCDA methods can be typically categorized as value measurement models; goal, aspiration, and reference level models; and outranking models [68]. For several applications, studies are found to use single MCDA methods. The application of MCDA is gaining attention in the energy domain, and often two or more MCDA methods are commonly utilized in energy sector applications. Boumaiza et al. used AHP, TOPSIS, SAW, and ELECTREII MCDA methods for analyzing the residential PV adoption. Such analyses aid in comparing the ranking of outcomes and covariation of ranking in alternative scenarios [69]. Ribeiro et al. evaluated future energy scenarios for the Portuguese power generation sector using MCDA [70]. The study utilized 13 criteria in the themes of economic, technical, quality of life of local populations, job market, and environmental issues. Zhao et al. applied
MCDA methods such as Data Envelopment Analysis (DEA) and Fuzzy AHP to determine the potential solutions to the production of hydrogen energy in Pakistan using various renewable energy resources [71]. The study performed the analysis with four primary criteria including social acceptance, economic, commercialization, and environmental. The results highlight that the production of hydrogen from biomass energy resources would be economically beneficial to Pakistan and is also a socially accepted energy resource. However, the production of hydrogen from wind energy resources is found to be the most efficient way. Browne et al. employed MCDA based on the NAIADE (Novel Approach to Imprecise Assessment and Decision Environments) software to analyze six policy measures for residential heating energy and domestic electricity consumption in an Irish city [72].

From the literature review, it can be observed that several studies are proposed for framing strategies, instituting policies, and simulating scenarios to decarbonize the energy sector effectively or to promote clean energy penetration. However, there are relatively few studies that provide the importance for specific geographical locations and investigate the energy transition ability of the country or location. Furthermore, the studies do not analyze the potential of the states or countries to undergo energy transition considering the various factors that can influence the clean energy transition. To address this knowledge gap, the authors aim to assess the clean energy transition potential of India by specifically focusing on seven major power-producing Indian states. This is achieved by using the MCDA methods such as TOPSIS and Multi-Objective Optimization Method by Ratio Analysis (MOORA) since these are simple and robust methods but are based on a different framework. Therefore, the results achieved through these methods might vary which will aid in understanding the influencing factors and criteria. Thus, a comparative analysis is performed to summarize the results obtained by each method. On the other hand, to direct the current power sector scenario towards a clean energy transition, allocating more weightage to the criteria that favor such a transition is vital. Therefore, the authors also utilized the Fuzzy AHP methodology to obtain a quantified weightage for each parameter considered in the analysis. The novelty of this study is as follows:

- Assessing the clean energy transition potential for seven significant power-producing states of India against 14 parameters.
- The analysis is performed from the dimensions of high carbon energy resource dependency, low carbon energy resource dependency, clean energy potential, and policy support.
- A progress-based analysis is accomplished in the policy support criterion.
- A comparative result analysis of TOPSIS and MOORA is performed.

3. Major Power-Producing Indian States

To obtain an unambiguous insight on the clean energy potential analysis in the Indian electricity sector, a state-specific focus is required. Further, analyzing the installed power generation capacity in each state will aid in identifying the major power-producing states. Figure 3 represents the state-wise cumulative installed power generation capacity in 2020. It can be inferred that seven major power-producing states cover 60% of the total installed power generation capacity of India. These states include Maharashtra, Gujarat, Tamil Nadu, Uttar Pradesh, Karnataka, Madhya Pradesh, and Andhra Pradesh. Therefore, assessing the clean energy transition potential in these states will contribute to shifting the electricity dependency from high carbon to low carbon energy resources strategically. A detailed investigation of the energy characteristics of these seven states is performed in this section.

3.1. Maharashtra

The state of Maharashtra has the highest installed power generation capacity of about 42.1 GW. The electricity mix of Maharashtra is dominated by coal, while the installed power generation capacity of wind is the highest among the renewable energy resources. Solar power generation is the least deployed among renewables and is growing rapidly [74]. Maharashtra is blessed with rich water bodies, and the total hydropower based installed
capacity is 34.27 GW. Altogether, the high carbon energy resource (HCER) installed capacity is 27.1 GW, while the low carbon energy resource (LCER) installed capacity is 15 GW which constitutes about 35.6% of the total installed power generation capacity in Maharashtra. The state aims to install an additional 17.385 GW of renewables within 2025. Of the 17.385 GW target, a major focus is on solar energy projects accounting for a target of 12.93 GW, followed by wind, cogeneration, small hydro, and solid-waste projects [75]. Further, the policy also proposed to invest $ 11.55 billion to 13.58 billion on the projects as well as to create job opportunities [75]. On the other hand, the state has a cumulative clean energy potential of 110 GW (constituting from solar, wind, and small hydropower) [76,77]. Tapping the potential of solar energy alone can shift the state’s electricity mix completely depending on LCER since the solar energy potential is 1.5 times higher than the current installed power generation capacity of Maharashtra.

Figure 3. State-wise installed power generation capacity in India up to 2020. Data source: [73].
3.2. Gujarat

Gujarat ranks second in having the most installed power generation capacity with a total installed capacity of 41.3 GW. In this state, the HCER installed capacity is 6 GW more than the LCER installed capacity, and LCER contributes 42.75% of the total installed capacity of Gujarat. Once again, the highest installed capacity is based on coal energy resources, but there exists 7 GW of difference between the coal dependence of Maharashtra and Gujarat with Maharashtra depending more on coal. The rapid deployment of wind and solar energy-based projects in recent years is the reason for a higher contribution of LCER when compared to Maharashtra [78]. As per the estimates of the state government, Gujarat’s renewable power generation capacity will increase to 38 GW by 2025 from 17 GW in 2021 [79]. The government also plans to reach a target of over 61 GW by 2030 [79]. These ambitious targets are backed up by mega green energy projects supported by policies’ initiatives and firm investments. Gujarat is rich in wind energy resources which has the potential to support 84 GW, while the solar energy potential is estimated to be 35.7 GW [76,77].

3.3. Tamil Nadu

Tamil Nadu is one of the crucial states that is blessed with various renewable energy resources. In this state, the LCER installed capacity is about 20.3 GW which constitutes 58.5% of the total installed capacity. Moreover, Tamil Nadu has the highest LCER installed capacity when compared to the considered seven states. Although coal-based installed capacity is the highest in Tamil Nadu, it is only 3.3 GW more than wind energy based installed capacity, positioning Tami Nadu as the top power producer from wind energy resources in India despite its wind energy potential being less than Gujarat, Maharashtra, Karnataka, and Andhra Pradesh. Further, the total wind and solar installed capacity surpasses the HCER installed capacity in Tamil Nadu. In recent years, the Government of Tamil Nadu is emphasizing solar energy projects, and the drafted policy (Tamil Nadu Solar Energy Policy 2019) aims to reach 9 GW of installed capacity from solar energy resources by 2023 from the current value of 4.7 GW [80]. The roadmap to this target also focuses on the consumer category of solar energy systems [80]. The estimated solar and wind energy potential in Tamil Nadu is 17.7 GW and 33.8 GW, respectively. A study also suggests that among the Southern states of India, Karnataka and Tamil Nadu have a better opportunity for tapping the solar energy potential for various applications [81].

3.4. Uttar Pradesh

Uttar Pradesh has the fourth-highest installed power generation capacity. This is the state where coal dominates other energy resources in the electricity mix with a significant difference. The HCER installation capacity is about 25.2 GW, while the LCER installation capacity is 5.2 GW, marking a contribution of only 17.1% in the total installed capacity. Uttar Pradesh has the least LCER installation capacity among the considered seven states of India. Among the renewables, bioenergy installation capacity (2.2 GW) is higher than the rest. Wind energy potential is negligible in this state, and thus, wind energy projects are not preferred in Uttar Pradesh. Solar energy constitutes 2 GW and is expected to witness a surge in the upcoming years. The hydro energy potential is also low in this state. Altogether, the cumulative clean energy potential in Uttar Pradesh constitutes about 24.5 GW which is lesser than the total installed capacity. In other words, even if the state taps all the clean energy resources, it is impossible to shift the power sector dependency on a high carbon energy resource completely. Therefore, in this scenario, complete decarbonization of the energy sector can be accomplished only by importing energy from neighboring states provided it can supply sufficient electricity generated from clean energy resources. The state aims to reach a solar installation capacity of 10.7 GW by 2022 [82] which is less likely to reach given the current contribution of solar energy projects.
3.5. Karnataka

The total installed power generation capacity of Karnataka is 29.8 GW, out of which 68.1% is constituted from LCER. In terms of the energy mix, Karnataka has the highest LCER penetration among the considered countries. However, coal is the major source that Karnataka depends on. Among the renewables, the solar energy resource has the highest installation capacity with almost 2 GW behind the coal-based installed power generation capacity. The hydropower, wind energy, and bioenergy based installed capacities in Karnataka are 4.9 GW, 5 GW, and 1.9 GW, respectively. The state envisions adding 10 GW of installed capacity based on renewable energy resources in the span of 5 years from 2021 to 2026 [83]. A study highlights that optimally handled Feed-in-tariff and Renewable Energy Certification policies will aid the energy companies to be benefited from the energy transition [84]. Further, to ensure economic growth during the energy transition, priority should be given to reductions in cross-subsidization, universal metering, the transmission of a reliable power supply to all the sectors, and optimization of the energy mix to substantiate efficient management of electricity production and consumption [85].

3.6. Madhya Pradesh

Madhya Pradesh is the state having the second least LCER based installed power generation capacity. The total installed capacity is about 29.6 GW, and coal constitutes around 21.9 GW of the installed capacity. Overall, the LCER installed capacity is 25% of the total installed capacity. Among the renewables, solar, wind, and hydro constitute almost equal contributions with an installed capacity of 2.6 GW, 2.5 GW, and 2.3 GW, respectively. The government of Madhya Pradesh fixed a target of reaching 12 GW of renewables by 2022 [86] which needs channelized policy support and investment. Madhya Pradesh has about 61.6 GW potential for solar energy, and therefore, the state should take steps to tap the solar energy potential. An analysis performed by Rout et al. indicates that the off-grid solar polygeneration system is feasible in Madhya Pradesh and Andhra Pradesh with the Benefit-Cost ratio of 1.25 and 1.32, respectively, while the corresponding annual levelized cost of energy is about 9.6 and 9.8 INR per kWh [87]. On the other hand, wind energy potential is comparatively low which constitutes about 10.4 GW.

3.7. Andhra Pradesh

The total installed power generation capacity of Andhra Pradesh constitutes about 7% of India’s total installed capacity. With coal being the highest contributor to the installed capacity, the dependency on other HCERs such as gas is also higher in this state. Overall, the HCER installed capacity is 16.5 GW, while the LCER installed capacity is 10.7 GW. Among the renewables, solar and wind energy resources have the highest installed capacity constituting about 4.3 GW and 4.1 GW, respectively. The government aims to install an additional 5 GW within the 5 years from 2019 to 2024 [88]. On investigating the clean energy potential in Andhra Pradesh, it is found that the state has abundant solar and wind energy potential of around 38.4 GW and 44.2 GW, respectively. The state has a mature renewable energy market, and policy schemes such as Feed-in-tariff is more effective in increasing the renewable energy penetration [89].

The installation power generation capacity of seven states of India is represented in Figure 4.
Figure 4. Installed power generation capacity in major power-producing states of India. Data source: [73].

4. Methodology

The methodology to analyze the clean energy transition potential can be perceived from the enumeration of assessment criteria and the elaboration of MCDA models.

4.1. Assessment Criteria

To analyze the clean energy transition potential of the considered seven states, it is of utmost importance to select the appropriate assessment criteria that cover the characteristics of the current clean energy scenario, energy transition potential, and policy support drivers. In a nutshell, these characteristics can be measured with the criteria such as high-carbon energy resource (HCER) dependency, low-carbon energy resource (LCER) dependency, clean energy resource potential, and policy support. In this section, the proposed four assessment criteria are elaborated in detail.

4.1.1. High-Carbon Energy Resource Dependency

The clean energy transition potential cannot be determined without assessing the degree of dependency on HCER by each major power-producing state. The greater the HCER installation capacity, the lesser is the clean energy transition potential since it will consume humungous efforts, investment, and targeted plans to reduce the dependency on HCER. Coal, gas, and diesel are the three HCER energy resources that are widely utilized in India for power production. To enumerate the HCER dependency criterion, the installed capacity of coal, gas, and diesel energy resources can be summed. However, the emission potential during energy conversion is higher for coal followed by gas and diesel (as shown in Table 1). In such a case, a weighted summation is required to depict the HCER dependency scenario accurately. In this study, the weightage is evaluated using the Fuzzy AHP methodology. Moreover, the weighted scenario will be supportive to highlight the impact of high emission energy resources because the weightage is derived from the degree of greenhouse gas (GHG) emissions that each resource produces in the entire lifecycle.
Table 1. Lifecycle GHG emission of various energy resources. Data source: [90,91].

| Commercially Available Power Generation Technologies | Life Cycle Emissions (g CO₂ e/kWh) |
|-----------------------------------------------------|------------------------------------|
| Coal                                                | 820                                |
| Gas                                                 | 490                                |
| Diesel                                              | 253                                |
| Nuclear                                             | 12                                 |
| Hydropower                                          | 24                                 |
| Wind energy                                         | 11                                 |
| Bioenergy                                           | 230                                |
| Solar energy                                         | 48                                 |

4.1.2. Low-Carbon Energy Resource Dependency

LCER installation capacity directly portrays the current clean energy scenario in the given state. This parameter acts as a baseline for policymaking to achieve the effective energy transition. The higher the LCER installation capacity, the higher is the clean energy transition potential since lesser progress will be required if LCER installed capacity dominates the energy mix. The predominantly utilized LCERs in India include solar, wind, biomass, hydro, and nuclear energy resources. Similar to the evaluation of the HCER dependency criterion, the LCER dependency criterion is obtained by evaluating the installed capacity of each LCER. Further, depending on the lifecycle emissions of each LCER, the weightage is obtained through the Fuzzy AHP methodology. Table 1 shows the lifecycle emission of various energy resources when utilized for power production. It can be observed that nuclear and wind energy resources have the least GHG emissions. Bioenergy has the highest median GHG emission among the LCER resources. Therefore, higher weightage is provided for nuclear and wind energy resources, while the lowest weightage is allocated for bioenergy resources. The rest of the LCERs such as hydro and solar are provided with a weightage according to the closeness of the emission values to the extreme values (i.e., high and low values).

4.1.3. Clean Energy Resource Potential

This criterion is crucial in evaluating the clean energy transition potential since it elucidates to what extent the energy transition can be accomplished in a given state. For instance, as discussed earlier, the state of Uttar Pradesh has a total clean energy resource potential less than that of cumulative installed power generation capacity (dominated by HCER) which indicates that it is infeasible to reach a complete energy transition. Thus, the clean energy resource potential parameter is of prime importance when compared to the rest of the assessment criteria. On analyzing the recent trends, it can be inferred that the government of India is focused on the solar and wind energy resources as they can be rapidly installed with less hindrance [73]. Further, the total bioenergy resource in India is 28 GW which is insufficient to satisfy the demand of each state [92]. Concerning the hydropower resource, the construction of large-scale hydropower resources is emphasized to a far lesser extent when compared to tapping the potential of small hydropower resources. On the other hand, the nuclear energy resource is difficult to quantify in terms of availability, and uncertainties in implementing nuclear power plants in India are high since it has already received social refusal [93]. Therefore, to witness a clean energy transition rapidly, this study focuses only on solar, wind, and small hydropower energy resources under the clean energy resource potential criterion. This is because the energy technologies based on these resources are widely accepted, rapidly emerging in the Indian energy market, and the Levelized Cost of energy is competitive to fossil fuels [94]. The weightage is also provided for each of these three clean energy resources while computing clean energy potential parameters. This weightage is based on the preference that India offers to these energy resources which can be inferred from the recent progress of installed capacity. It can be observed that solar and wind have been given pivotal significance, while small hydropower
is given lesser importance, and the decision matrix in the Fuzzy AHP methodology is constructed accordingly (Refer to Appendix A, Table A4).

4.1.4. Policy Support

Policy support is a qualitative term, but the intensity of support can be quantified based on the progress made and target that each state proposes. Policy support serves as a criterion that establishes certainty in the energy transition. In other words, policy support can accelerate the clean energy transition, and therefore, clean energy transition potential is higher in the state where policy support is higher. While the clean energy potential criterion is built on the availability of energy resources, policy support is designed to emphasize the implementation ability of each state. The policy support criteria can be evaluated based on three parameters—the annual HCER installation capacity rate, annual LCER installation capacity rate, and performance gap.

The annual HCER installation capacity rate is the parameter that is obtained by finding the average per year increase in the HCER installation capacity from 2018 to the present. Similarly, the annual LCER installation capacity rate parameter can be calculated by obtaining the LCER installation capacity data corresponding to 2018 and current data. The annual HCER installation capacity parameter will aid in assessing the policy support in installing the dependency on the HCER, while the annual LCER installation capacity parameter highlights the progressing capacity of the state towards clean energy which, in turn, maps the observable results of policy support in the energy transition.

The performance gap is the parameter that aims to quantify the performance of the state with respect to the clean energy policy targets that the state proposes. From the targets fixed by the seven major power-producing states, it can be inferred that there exist two types of clean energy target frameworks. One is based on reaching a targeted cumulative installation capacity, and another type deals with the addition of a certain quantity of clean energy-based installed power generation capacity within a specific time frame. For instance, Gujarat aims to reach 38 GW of renewable-based installed capacity from the current value of 15.2 GW, while Maharashtra drafts a policy target to install an additional 17 GW to the existing capacity. The performance gap can be determined by utilizing the annual LCER installation capacity rate and calculating the required installed capacity rate. The required installed capacity rate is enumerated by finding the required additional installation capacity from the present year to the target year and dividing it by policy span. Altogether, the performance gap is considered as the ratio of the required additional installation capacity to the annual LCER installation capacity. If the performance gap is less than 1, then the progress of the state is well supported by the policy to achieve the proposed target. If the performance gap is greater than 1, then the proposed target needs additional policy support, and a higher performance gap might also indicate an unrealistic target given the current progress.

The data corresponding to each parameter under each criterion are represented in Table 2. As a whole, the clean energy transition potential is assessed for seven major power-producing states of India based on 4 criteria and 14 parameters. The clean energy transition potential assessment framework is represented in Figure 5.

4.2. Multi-Criteria Decision Analysis (MCDA) Models

There exist numerous parameters, and each parameter can be beneficial or non-beneficial to the assessment of the clean energy transition potential. For instance, HCER dependency is a non-beneficial criterion since the higher the HCER score, the lower is the clean energy transition potential. Therefore, for a higher clean energy transition potential, a higher score in beneficial criteria and a lower score in the non-beneficial criteria are required. Since the nature of the parameters considered varies, and numerous parameters exist, the objective of assessing the clean energy transition potential in major power-producing states can be accomplished by using the Multi-Criteria Decision Analysis (MCDA) methodology. In this study, MCDA models are utilized for two purposes: (i) for evaluating the weightage
to the parameters and criteria, (ii) for assessing the clean energy transition potential of seven Indian states. The former purpose of weightage determination is performed using the Fuzzy AHP model, while the latter purpose is accomplished by utilizing TOPSIS and MOORA MCDA methods. The flowchart of the MCDA process involving Fuzzy AHP, TOPSIS, and MOORA is depicted in Figure 6.

Table 2. Data corresponding to various criteria and parameters (decision matrix).

| Criteria Parameters | Major Power-Producing States of India |
|---------------------|--------------------------------------|
|                     | Maharashtra | Gujarat | Tamil Nadu | Uttar Pradesh | Karnataka | Madhya Pradesh | Andhra Pradesh |
| High-carbon energy resource dependency (GW) | Coal | 23.856 | 16.092 | 13.160 | 23.729 | 9.480 | 21.950 | 11.590 |
|                     | Gas | 3.207 | 7.551 | 1.027 | 1.493 | 0.000 | 0.025 | 0.000 | 0.000 | 4.899 |
|                     | Diesel | 0.000 | 0.000 | 0.212 | 0.000 | 0.025 | 0.000 | 0.037 |
| Low-carbon energy resource dependency (GW) | Nuclear | 1.400 | 0.440 | 2.440 | 0.440 | 0.880 | 0.000 | 0.000 |
|                     | Hydropower | 3.428 | 2.073 | 2.301 | 0.551 | 4.970 | 2.335 | 1.772 |
|                     | Solar | 2.541 | 6.093 | 4.738 | 2.032 | 7.512 | 2.674 | 4.381 |
|                     | Wind | 5.013 | 8.953 | 9.847 | 0.000 | 5.039 | 2.520 | 4.097 |
|                     | Bioenergy | 2.632 | 0.100 | 1.040 | 2.180 | 1.902 | 0.128 | 0.536 |
| Clean energy potential (GW) | Solar energy potential | 64.320 | 35.770 | 17.670 | 22.380 | 24.700 | 61.660 | 38.440 |
|                     | Wind energy potential | 45.390 | 84.430 | 33.790 | 1.260 | 55.850 | 10.480 | 44.220 |
|                     | Small hydropower potential | 0.786 | 0.202 | 0.604 | 0.461 | 3.726 | 0.820 | 0.409 |
| Policy support | Annual HCER installation capacity rate | −0.457 | 0.200 | 0.133 | 0.660 | −0.043 | 1.208 | 0.006 |
|                     | Annual LCER installation capacity rate | 0.427 | 2.448 | 1.271 | 0.463 | 0.942 | 0.370 | 0.631 |
|                     | Performance gap | 10.167 | 2.325 | 1.676 | 9.370 | 2.123 | 17.768 | 2.640 |

Figure 5. Framework for assessing clean energy transition potential.
4.2. Multi-Criteria Decision Analysis (MCDA) Models

There exist numerous parameters, and each parameter can be beneficial or non-beneficial to the assessment of the clean energy transition potential. For instance, HCER dependency is a non-beneficial criterion since the higher the HCER score, the lower is the clean energy transition potential. Therefore, for a higher clean energy transition potential, a higher score in beneficial criteria and a lower score in the non-beneficial criteria are required. Since the nature of the parameters considered varies, and numerous parameters exist, the objective of assessing the clean energy transition potential in major power-producing states can be accomplished by using the Multi-Criteria Decision Analysis (MCDA) methodology. In this study, MCDA models are utilized for two purposes: (i) for evaluating the weightage to the parameters and criteria, (ii) for assessing the clean energy transition potential of seven Indian states. The former purpose of weightage determination is performed using the Fuzzy AHP model, while the latter purpose is accomplished by utilizing TOPSIS and MOORA MCDA methods. The flowchart of the MCDA process involving Fuzzy AHP, TOPSIS, and MOORA is depicted in Figure 6.

Figure 6. MCDA flowchart for assessing clean energy transition potential.

4.2.1. Fuzzy AHP

Fuzzy AHP is a widely used MCDA method because of its capability to handle uncertainties in decision-making problems. In this study, Fuzzy AHP is utilized to determine the weightage of each primary level criteria and secondary level parameters. The weightage determination via Fuzzy AHP can be enumerated by utilizing the following steps.

- **Step 1: Pairwise comparison matrix**

  The pairwise comparison matrix consists of comparison scores for n x n parameters. The comparison score is based on Saaty’s comparison scale [95]. In this matrix, the $A_{ij}$ element is always the reciprocal of the $A_{ij}$ element where $A_{ij}$ represents the element of the matrix corresponding to the $i$th row and $j$th column. The pairwise comparison matrix is mathematically represented in Equation (1).

  $$A_{ij} = \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1n} \\ A_{21} & A_{22} & \cdots & A_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ A_{n1} & A_{n2} & \cdots & A_{nn} \end{bmatrix} \tag{1}$$

- **Step 2: Fuzzification**

  Each element of the pairwise comparison matrix is fuzzified into Triangular Fuzzy Numbers (TFN) which indicate the triangle corner points represented in the format of $(a, b, c)$. Equation (2) represents the fuzzification process with constraints.
\[ A_{ij} = (l_{ij}, m_{ij}, u_{ij}) \] and \[ A_{ij}^{-1} = (l_{ij}, m_{ij}, u_{ij})^{-1} = \left( \frac{1}{u_{ij}}, \frac{1}{m_{ij}}, \frac{1}{l_{ij}} \right), \text{ such that } l_{ij} < m_{ij} < u_{ij} \] (2)

- Step 3: Aggregated fuzzy decision matrix

The fuzzified pairwise comparison matrix is aggregated through the geometric mean which is represented in Equation (3).

\[ r_i = (l_i, m_i, u_i) = \sqrt[n]{\prod_{i=1}^{n} A_{ij}} \] (3)

- Step 4: Fuzzy weight determination

The ratio of the \( A_{ij} \) element of an aggregated fuzzy decision matrix to the summation of all the elements in the \( j \)th column will yield fuzzy weights. This is mathematically shown in Equation (4).

\[ w_i = \frac{r_i}{\sum_{i=1}^{n} r_i} = r_i \times \left( \sum_{i=1}^{n} r_i \right)^{-1} \] (4)

where \( w_i \) is the fuzzy weight of criteria \( i \).

- Step 5: Defuzzification

The obtained fuzzy weights are subjected to defuzzification by using the expression in Equation (5).

\[ \text{Centre of weight (} M_i \text{)} = \frac{l_{\phi_i} \oplus m_{\phi_i} \oplus u_{\phi_i}}{3} \] (5)

where \( M_i \) is the weight after defuzzification corresponding to the \( i \)th parameter.

- Step 6: Normalization of weights

Normalization is performed if the sum of weights after defuzzification is not equal to 1. It is performed by utilizing Equation (6).

\[ N_i = \left( \frac{M_i}{\sum_{i=1}^{N} M_i} \right) \] (6)

where \( N_i \) is the normalized weightage obtained through Fuzzy AHP analysis for the given \( i \)th parameter.

4.2.2. TOPSIS

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is a MCDA method originally proposed by Hwang and Yoon to make decisions among various alternatives [96]. In brief, TOPSIS provides an aggregated result by comparing the geometric distance between each alternative and the best alternative. TOPSIS is one of the compensatory methods where a poor performance in one criterion can be compensated by good performance in other criteria, altogether making a robust and realistic evaluation. The best alternative ranked by the TOPSIS method should have the least distance from the positive ideal solution, while it should have the highest distance from the negative ideal solution [97]. The TOPSIS methodology is performed by following a step-wise procedure [98].

- Step 1: Decision matrix
A decision matrix is a \( m \times n \) matrix where rows and columns correspond to alternatives and parameters, respectively. \( a_{ij} \) is the element of the decision matrix representing the \( i \)th alternative’s score against the \( j \)th parameter. The decision matrix is shown in Equation (7).

\[
a_{ij} = \begin{bmatrix}
a_{11} & a_{12} & \ldots & a_{1n} \\
a_{21} & a_{22} & \ldots & a_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
a_{m1} & a_{m2} & \ldots & a_{mn}
\end{bmatrix}
\] (7)

- **Step 2: Normalized decision matrix**

Since the parameters considered for analysis have incongruous dimensions, normalization is required. Normalization of the decision matrix is accomplished by using Equation (8).

\[
r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a_{ij}^2}}
\] (8)

The element \( r_{ij} \) corresponds to the normalized decision matrix element.

- **Step 3: Weighted normalized decision matrix**

The weighted normalized decision matrix is obtained by multiplying the weightage corresponding to each parameter to the elements of the normalized decision matrix. This is expressed in Equation (9).

\[
v_{ij} = w_j r_{ij}
\] (9)

where \( w_j \) is the weightage obtained by the Fuzzy AHP method in this study; \( v_{ij} \) is the element of the weighted normalized decision matrix.

- **Step 4: Enumerate positive-ideal solution (PIS) and negative-ideal solution (NIS)**

The best performing and worst performing alternatives corresponding to each criterion are regarded as PIS and NIS, respectively, for each criterion. The determination of PIS and NIS depends on the nature of criteria, i.e., beneficial or non-beneficial criteria. For beneficial criteria, PIS is the alternative having a maximum score, and NIS is the alternative having a minimum score and is vice-versa for non-beneficial criteria. The mathematical representation for the determination of PIS and NIS is shown in Equations (10) and (11).

\[
A^* = \left\{ \begin{array}{l}
\max v_{ij}, \text{ for benefit criteria} \\
\min v_{ij}, \text{ for non-beneficial criteria}
\end{array} \right\} = \{v_{1}^*, v_{2}^*, \ldots, v_{n}^* \}
\] (10)

\[
A^- = \left\{ \begin{array}{l}
\min v_{ij}, \text{ for benefit criteria} \\
\max v_{ij}, \text{ for non-beneficial criteria}
\end{array} \right\} = \{v_{1}^-, v_{2}^-, \ldots, v_{n}^- \}
\] (11)

where \( A^* \) and \( A^- \) are the PIS and NIS, and \( n \) represents number of alternatives.

- **Step 5: Determine the distance of each alternative from PIS and NIS**

The alternative’s distance from PIS and NIS can be computed by using Equations (12) and (13), respectively.

\[
S_i^+ = \sqrt{\sum_{j=1}^{m} (v_{ij} - v_{ij}^+)^2}
\] (12)

\[
S_i^- = \sqrt{\sum_{j=1}^{m} (v_{ij} - v_{ij}^-)^2}
\] (13)

where \( m \) represents the total number of criteria.

- **Step 6: Calculate the closeness coefficient**
The closeness coefficient represents the aggregated score which is calculated based on the distance of each alternative from PIS and NIS. It is mathematically expressed in Equation (14).

$$CC_i = \frac{S_i^+}{S_i^+ + S_i^-}$$ (14)

where $CC_i$ is constructed such that its value varies within the range between 0 and 1.

- **Step 7: Ranking of alternatives**

  Since the closeness coefficient produces an aggregated score, the final ranking is accomplished based on the $CC_i$ score. The higher the $CC_i$ score, the better is the performance of the state. A $CC_i$ score near 1 and 0 indicates that it is near to PIS and NIS, respectively.

### 4.2.3. MOORA

Multi-objective optimization based on ratio analysis (MOORA) is a MCDA method where the optimum solution is favored by aggregating maximum benefits and minimum costs. In this study, a ratio system type of the MOORA method is utilized [99]. The algorithm of MOORA is detailed as follows:

- **Step 1: Formulation of decision matrix**

  A decision matrix is a $m \times n$ matrix where rows and columns correspond to alternatives and parameters, respectively. $x_{ij}$ is the element of the decision matrix representing the $i^{th}$ alternative’s score against the $j^{th}$ parameter. The decision matrix is shown in Equation (15).

$$x_{ij} = \begin{bmatrix} x_{11} & x_{12} & \ldots & x_{1n} \\ x_{21} & x_{22} & \ldots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \ldots & x_{mn} \end{bmatrix}$$ (15)

- **Step 2: Normalized decision matrix**

  The normalization is performed to each element of the decision matrix by dividing that element with the root sum square of all the elements in the column in which the element is present. This is expressed as Equation (16).

$$x_{ij}^* = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$$ (16)

where $x_{ij}^*$ is the element of the normalized decision matrix.

- **Step 3: Weighted normalized decision matrix**

  The weighted normalized decision matrix is obtained by multiplying the weightage corresponding to each parameter to the elements of the normalized decision matrix. This is expressed in Equation (17).

$$W_{ij} = w_j x_{ij}^*$$ (17)

where $w_j$ is the weightage obtained by the Fuzzy AHP method in this study; $W_{ij}$ is the element of the weighted normalized decision matrix.

- **Step 4: Enumeration of optimum score**

  The optimum score is obtained by summing the weighted normalized scores of all the beneficial criteria and subtracting the weighted normalized scores of all the non-beneficial criteria. The mathematical expression for the same is shown in Equation (18).

$$y_i = \sum_{j=1}^{B} W_{ij} - \sum_{j=1}^{N} W_{ij}$$ (18)
where \( y_i \) is the optimized score; \( g \) is the total number of beneficial parameters; and \( n \) is the total number of non-beneficial parameters. In this study, \( g \) and \( n \) values are 9 and 5, respectively.

- Step 5: Ranking of alternatives
  
The ranking is accomplished based on the optimized score, \( y_i \). The greater the value of \( y_i \), the higher is the performance of the corresponding state.

5. Results

The clean energy transition potential of major power-producing states of India is determined by utilizing the MCDA method in which the assessment includes 4 criteria and 14 parameters. The results are categorized as weightage results, MCDA results, and the comparative analysis.

5.1. Fuzzy AHP Weightage

The pairwise comparison decision matrix for each Fuzzy AHP analysis is represented in Appendix A, Tables A1–A5. The weightage is evaluated in two stages, i.e., primary and secondary level weightage where the primary level corresponds to weightage for various criteria, while the secondary level refers to weightage to parameters within each criterion. The final weightage is calculated by multiplying the weightage values obtained at both levels. The resulting final weightage for each parameter is shown in Table 3. The highest weightage is resulted for solar and wind energy potential parameters, while the lowest weightage value is obtained for the bioenergy based LCER installation capacity. This maps the Indian clean energy scenario where recent efforts are concentrated on solar and wind energy. On the other hand, policy support parameters are given priority to improve the progress that each state makes. Coal is utilized to a higher extent in the Indian power sector, and thus, the resulting higher weightage to the coal parameter under the HCER installation capacity criterion will diminish the performance score of each state in the MCDA since this parameter is treated as a non-beneficial parameter. Therefore, the resulting weightage depicts the relation between the clean energy transition potential and each criterion. For instance, clean energy potential is the foundation for assessing the clean energy transition potential, and thus, higher weighted parameters are found in this criterion. Policy support fosters progress, and it is given second preference after the clean energy potential criterion. The HCER and LCER installation capacity mark the current scenario, and it supports only to assess the state’s present status, and therefore, these criteria are given a lesser weightage.

Table 3. Fuzzy AHP weightage results.

| Criteria | Parameters | Secondary Level Weightage | Primary Level Weightage | Aggregated Weightage |
|----------|------------|---------------------------|-------------------------|---------------------|
| High-carbon energy resource dependency | Coal | 0.7273 | 0.1115 | 0.0811 |
| | Gas | 0.1896 | | 0.211 |
| | Diesel | 0.0831 | | 0.093 |
| Low-carbon energy resource dependency | Nuclear | 0.3208 | 0.1211 | 0.0389 |
| | Hydropower | 0.2058 | 0.0249 | |
| | Solar | 0.1229 | 0.0149 | |
| | Wind | 0.3208 | 0.0389 | |
| | Bioenergy | 0.0297 | 0.0036 | |
| Clean energy potential | Solar energy potential (GW) | 0.4424 | 0.4529 | 0.2004 |
| | Wind energy potential (GW) | 0.4424 | 0.2004 | |
| | Small hydropower potential (GW) | 0.1151 | 0.0522 | |
| Policy support | Annual HCER Installation capacity rate | 0.3068 | 0.0965 | |
| | Annual LCER Installation capacity rate | 0.5202 | 0.1636 | |
| | Performance gap | 0.1730 | 0.0544 | |
5.2. TOPSIS Results

Table 2 serves as the decision matrix for the TOPSIS method. The weighted normalized decision matrix, along with PIS and NIS, is shown in Appendix A, Table A6. The computed distance from PIS and NIS, closeness coefficient value, and alternative’s ranking are represented in Table 4.

Table 4. Results of TOPSIS.

| States            | \(S_i^+\) | \(S_i^-\) | \(CC_i\) | Rank |
|------------------|-----------|-----------|---------|------|
| Maharashtra      | 0.1358    | 0.1591    | 0.5395  | 2    |
| Gujarat          | 0.0885    | 0.1944    | 0.6870  | 1    |
| Tamil Nadu       | 0.1454    | 0.1168    | 0.4455  | 5    |
| Uttar Pradesh    | 0.2107    | 0.0459    | 0.1788  | 7    |
| Karnataka        | 0.1226    | 0.1432    | 0.5388  | 3    |
| Madhya Pradesh   | 0.2077    | 0.0844    | 0.2890  | 6    |
| Andhra Pradesh   | 0.1415    | 0.1207    | 0.4603  | 4    |

It can be observed that Gujarat has the highest clean energy transition potential when compared to other major power-producing states of India. This is because Gujarat’s score for each parameter is the PIS or is near the PIS (i.e., second or third highest) in most cases. This is evident from the distance from PIS and NIS values corresponding to Gujarat in Table 4. In other words, the distance from PIS is a minimum, while the distance from NIS is a maximum in the case of Gujarat when compared to other states considered for the analysis. The second and third rank is obtained by Maharashtra and Karnataka, respectively. On comparing these two states, it can be found that the distance from the PIS value of Maharashtra is more than that of Karnataka. Besides, Maharashtra has a much larger distance from the NIS value than Karnataka, and thus, Maharashtra obtains the second rank.

The difference between the scores of Gujarat and Maharashtra is higher since Gujarat has the highest clean energy potential, especially wind energy potential being the highest among seven states which is also the highest weighted parameter in the analysis. On the other hand, the difference between the scores of Maharashtra and Karnataka is less, but there is no single reason for such a small difference since the results represent an aggregated score. As an example, Maharashtra has a significantly higher wind and solar energy potential as well as an annual HCER installation capacity rate. Meanwhile, Karnataka scores much higher in parameters such as solar energy installed capacity, reduced coal usage, the performance gap, and the annual LCER installation capacity rate. This induces conflicting decisions, and thus, MCDA proves useful in such a scenario to provide a big picture of clean energy transition potential.

The least score is obtained by Uttar Pradesh since it has the highest distance from PIS and lowest distance from NIS. This is because Uttar Pradesh performs poorly under policy support criteria, and to add upon it, the total clean energy potential is less than its total energy installation capacity marking an unfavorable clean energy transition potential.

5.3. MOORA Results

Table 2 serves as the decision matrix for the MOORA method. The normalized decision matrix is represented in Appendix A, Table A7. The optimized score and the ranking of alternatives are presented in Table 5.

The results indicate that Gujarat, Karnataka, and Maharashtra obtain the first, second, and third rank, respectively, in clean energy transition potential. Despite Gujarat having a higher clean energy transition potential, its dependency on coal and gas should be reduced to witness the energy transition. The gas dependency of Gujarat is the highest when compared to other states, while the annual HCER installation capacity rate is 0.2 GW which still indicates an increasing trend. In MOORA analysis, Karnataka’s score is greater than Maharashtra since Karnataka leads Maharashtra in many parameters with a considerable
difference. Tamil Nadu attains the fourth rank, and this is attributed to a comparatively less clean energy potential which pulls down the performance of Tamil Nadu in clean energy transition potential. On the other hand, Tamil Nadu is the only state that has the least performance gap but is still slightly greater than 1, indicating the requirement of improved performance in installing additional clean power generation capacities to reach the proposed target of reaching 9 GW of solar energy projects. Further, the nuclear and wind energy based LCER installation capacity is highest in Tamil Nadu which would give a boost in the final optimized score. Therefore, the score of policy support and LCER installation capacity favored Tamil Nadu to reach the fourth rank despite having the second least clean energy potential among the considered seven states. Andhra Pradesh attains the fifth rank, and this is favored primarily by a higher clean energy potential. Apart from this criterion, the performance of Andhra Pradesh is moderate in the rest of the criteria. Similar to Andhra Pradesh, Madhya Pradesh exhibits moderate performance in HCER and LCER installation capacity but has lesser clean energy potential than Andhra Pradesh. Further, Madhya Pradesh has the highest annual HCER installation capacity rate and annual lowest LCER installation capacity rate as well as the widest performance gap among the seven states which altogether marks the least score under policy support criteria. Thus, Madhya Pradesh scores considerably less than Andhra Pradesh. Meanwhile, Uttar Pradesh has the lowest optimized score, and it is ascribed to the least clean energy potential.

Table 5. Results of MOORA method.

| States          | Optimized Score | Rank of States |
|-----------------|-----------------|----------------|
| Maharashtra     | 0.2286          | 3              |
| Gujarat         | 0.3136          | 1              |
| Tamil Nadu      | 0.1857          | 4              |
| Uttar Pradesh   | −0.0230         | 7              |
| Karnataka       | 0.2653          | 2              |
| Madhya Pradesh  | 0.0181          | 6              |
| Andhra Pradesh  | 0.1632          | 5              |

5.4. Comparative Analysis

The TOPSIS method depends on each alternative score corresponding to each criterion since the closeness coefficient depends on the distance between PIS and NIS which, in turn, depends on relative scores of alternatives in a given criterion. However, the MOORA method does not depend on the performance of each alternative in the given criteria, and this gives a major difference in assessment between the considered MCDA methods. Therefore, the variations in the rank resulted. The comparison of the rank of seven states obtained by using TOPSIS and MOORA MCDA methods is presented in Figure 7. In both cases, Gujarat achieved the top score, Madhya Pradesh obtained the sixth rank, and Uttar Pradesh attained the least score. On the other hand, the ranks of the rest of the four states vary only by one rank. This is due to the methodological difference in calculating the final scores. The TOPSIS method utilizes a relative comparison approach, while MOORA emphasizes synergic and trade-off effects induced by each criterion on the final objective. As a whole, it is obvious that Gujarat has the highest clean energy transition potential, and thus, with the proper policy support and channelized investment, Gujarat can become the clean energy powerhouse of India.
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6. Policy Implications

The policy implications for seven major producing states are illustrated as follows:

- **Gujarat** emerged to be the state having the highest clean energy transition potential. Although the annual HCER installation capacity is less in Gujarat, it has the higher coal dependency and highest gas dependency in the country. Gujarat excels in the efforts to promote renewables as this is evident in annual LCER installation capacity, but the performance gap is more than 2 which indicates that higher progress is required to achieve the target fixed by the state. Therefore, the policy should be focused on accelerating the focus on renewables. This can be accomplished by tapping the abundant onshore and offshore wind energy potentials in Gujarat. The policy draft should emphasize more on wind energy with a clear roadmap towards the target. Nevertheless, the focus on solar energy technologies can be prioritized in the industrial and residential sectors in Gujarat.

- **Maharashtra**, being the highest energy producer in India, should focus on the energy transition with transformative energy policies where the energy transformation is underpinned by renewables to the extent that it is sufficient to decouple the fossil fuel dependency. A two-phase policy is required to entrench the energy transition where the first phase should emphasize promoting and accelerating renewable energy penetration, while the second phase should be focused on phasing out coal and gas power plants. The state of Maharashtra has abundant clean energy potential both in terms of solar and wind energy. However, the annual LCER installation capacity rate is less than 0.5 GW. On the other hand, the annual HCER installation capacity rate witnesses a negative trend, and the phased-out HCER installation capacity rate is higher than the LCER installation capacity rate. This indicates a poor focus on renewable energy, and therefore, policies should attract investors and contracts to increase the renewable energy penetration rapidly in the upcoming years. Further,
the performance gap is more than 10 which indicates an unrealistic target set by the
government. Hence, a refined renewable energy target, as well as a roadmap to achieve
the same in the stipulated time frame, should be given importance.

- Karnataka has the highest LCER penetration in the energy mix, and the state has the
  highest contributions from hydropower and solar energy resources when compared to
  the considered states. The energy mix of the state is dominated by LCER, but efforts
  are required to reduce the dependency on coal despite being the only state having its
  coal dependency of less than 10 GW. The state’s annual HCER installation capacity
  witnesses a negative trend, and the annual LCER is near 1 GW. Thus, the policies
  should focus on increasing the installation capacity rate of renewables by tapping
  the potential of solar, wind, and small hydropower resources. A specific focus on
  residential solar energy systems will be conducive to closing the performance gap
  between the current installation rate and the fixed target. On the other hand, the state
can also focus on energy trade with the neighboring Southern and Northern states to
  promote the utilization of renewable energy without curtailment.

- Tamil Nadu has the highest LCER installation capacity among the seven states con-
sidered for the analysis. On analyzing the policy parameters of Tamil Nadu, it can be
observed that the state has a low annual HCER installation capacity rate, and the an-
nual LCER installation capacity rate is about 1.2 GW. In addition, the performance gap
is the lowest among the seven states. Altogether, the policy support for Tamil Nadu is
good enough to witness an energy transition, but the policy aspect fails to focus on
reducing the expansion of fossil fuel based energy resources. The performance of Tamil
Nadu is impressive in tapping wind energy despite its overall clean energy potential
being around 52 GW which is lower than five considered states. In the upcoming
years, the state should focus on expanding its solar energy harvesting capacity.

- Andhra Pradesh has a total clean energy potential of 83 GW, but the energy mix is
dominated by HCER, and the annual LCER installation capacity rate is just 0.6 GW.
From the policy target framed by the government, it is observed that the target is
less ambitious when compared to other states. The performance gap is greater than
2 because of its lower annual LCER installation capacity rate. Therefore, the policy
aspect for Andhra Pradesh should emphasize accelerating the wind and solar energy
projects with a revamped target.

- The energy mix of Madhya Pradesh constitutes 25.8% of LCER, and the state heavily
depends on coal. Madhya Pradesh has an enormous solar energy potential of about
61.6 GW, but the total solar installed capacity is just 2.6 GW. The performance gap
is the highest in this state due to lesser LCER installation, marking ineffective policy
planning. The state can traverse in the path of energy transition only if the policy
measures focus on promoting solar energy projects. The state is far from phasing
out fossil fuels due to their very high dependency. Therefore, carbon tax policy
can effectively generate revenue for the state which can be invested in developing
clean energy projects. Further, incentive schemes on the solar energy projects and
attractive feed-in-tariff rates should be inclusive to promote solar energy penetration
in Madhya Pradesh.

- Uttar Pradesh has the least clean energy transition potential, and, indeed, the state’s
capacity would not support a complete energy transition. The only possible way
for the state to achieve 100% dependency on LCER is by energy trading with the
neighboring states. This scenario is less likely due to economic constraints, uncertainty
in energy security, and the limitations that the government will face. Therefore, the
policy aspect should focus on maximizing energy efficiency, utilizing polygeneration
and cogeneration systems. Moreover, carbon capture and storage, as well as carbon
capture and utilization technologies, can be integrated into existing fossil fuel based
power plants to reduce emissions. On the other hand, the state should tap as much
solar energy as possible through numerous green energy projects.
7. Conclusions

India is the third-largest electricity consuming country in the world, and the energy mix in the power sector is hugely dominated by coal (about 71%). To accelerate the government’s action further, a comprehensive analysis of each state’s clean energy characteristics is to be assessed. In line with this, the proposed study evaluates the clean energy transition potential of seven major power producing states in India. These seven states include Maharashtra, Gujarat, Tamil Nadu, Uttar Pradesh, Karnataka, Madhya Pradesh, and Andhra Pradesh.

To analyze the clean energy transition potential, four criteria are put forward which include high carbon energy resource dependency, low carbon energy resource dependency, clean energy potential, and policy support. The weightage is provided in a way that the state having higher clean energy potential and policy support will possess higher clean energy transition potential. Altogether, the analysis is substantiated with four criteria and fourteen parameters where the weightage is provided by using Fuzzy Analytic hierarchy process methodology.

The alternatives are evaluated for clean energy transition potential by employing TOPSIS and the MOORA multi-criteria decision analysis methodology. The results indicate that Gujarat has the highest clean energy transition potential which means that Gujarat might emerge as the clean energy hub of India, given its clean energy potential, policy support, and recent progress in the LCER installation capacity rate. The second and third position is attained by Maharashtra and Karnataka, respectively, in TOPSIS and vice-versa rank in MOORA. Uttar Pradesh has the least clean energy transition potential such that the state’s clean energy potential does not support the current installed capacity. The proposed methodology to analyze the clean energy transition potential can be extended to any country in the world. The policy implication corresponding to each state is also summarized in this study.

To conclude, India has a rich clean energy resource potential, and tapping those resources, especially in the top five states in the performed analysis, can cover about twice the installation capacity that is currently implemented. Therefore, the central and state government should emphasize feasible policy to promote solar and wind energy harvesting technologies in the upcoming years.

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Appendix A

Table A1. Pairwise comparison decision matrix of four criteria for Fuzzy AHP weightage determination.

| Criteria          | HCER | LCER | Clean Energy Potential | Policy Support |
|-------------------|------|------|------------------------|----------------|
| HCER              | 1    | 1    | 0.25                   | 0.33           |
| LCER              | 1    | 1    | 0.33                   | 0.33           |
| Clean energy potential | 4    | 3    | 1                      | 2              |
| Policy support    | 3    | 3    | 0.50                   | 1              |
Table A2. Pairwise comparison decision matrix of three parameters of HCER dependency criteria for Fuzzy AHP weightage determination.

|        | Coal | Gas  | Diesel |
|--------|------|------|--------|
| Coal   | 1    |      | 7      |
| Gas    | 0.20 | 1    | 3      |
| Diesel | 0.14 | 0.33 | 1      |

Table A3. Pairwise comparison decision matrix of five parameters of LCER dependency criteria for Fuzzy AHP weightage determination.

|            | Nuclear | Hydropower | Solar | Wind       | Bioenergy |
|------------|---------|------------|-------|------------|-----------|
| Nuclear    | 1       | 2          | 3     | 1          | 9         |
| Hydropower | 0.50    | 1          | 2     | 0.50       | 7         |
| Solar      | 0.33    | 0.50       | 1     | 0.33       | 5         |
| Wind       | 1       | 2          | 3     | 1          | 9         |
| Bioenergy  | 0.11    | 0.14       | 0.20  | 0.11       | 1         |

Table A4. Pairwise comparison decision matrix of three parameters of clean energy potential criteria for Fuzzy AHP weightage determination.

| Solar Energy Potential | Wind Energy Potential | Small Hydropower Potential |
|------------------------|-----------------------|-----------------------------|
| Solar energy potential | 1                     | 1                           |
| Wind energy potential  | 1                     | 1                           |
| Small hydropower potential | 0.25          | 0.25                         |

Table A5. Pairwise comparison decision matrix of three parameters of policy support criteria for Fuzzy AHP weightage determination.

| Annual HCER Installation Capacity Rate | Annual LCER Installation Capacity Rate | Performance Gap |
|---------------------------------------|---------------------------------------|------------------|
| Annual HCER Installation capacity rate | 1                                     | 0.50             |
| Annual LCER Installation capacity rate | 2                                     | 1                |
| Performance gap                       | 0.50                                  | 0.33             |

Table A6. Weighted normalized decision matrix, PIS, and NIS values in the TOPSIS method.

| Weighted Normalized Performance Value | PIS  | NIS  |
|---------------------------------------|------|------|
| Maharashtra                          |      |      |
| 0.0406                                | 0.0161 | 0.0406 |
| 0.0070                                | 0.0000 | 0.0164 |
| 0.0000                                | 0.0000 | 0.0022 |
| 0.0181                                | 0.0057 | 0.0024 |
| 0.0115                                | 0.0000 | 0.0019 |
| 0.0031                                | 0.0073 | 0.0001 |
| 0.0123                                | 0.0022 | 0.0032 |
| 0.1170                                | 0.0651 | 0.0415 |
| 0.0730                                | 0.1358 | 0.0898 |
Table A6. Cont.

| Weighted Normalized Performance Value | PIS     | NIS     |
|--------------------------------------|---------|---------|
| Maharashtra                          | 0.0103  | 0.0026  |
| Gujarat                              | 0.0079  | 0.0060  |
| Tamil Nadu                           | 0.0486  | 0.0107  |
| Uttar Pradesh                        | 0.0053  | 0.0486  |
| Karnataka                            | 0.0107  | 0.00004 |
| Madhya Pradesh                       | 0.0004  | 0.0793  |
| Andhra Pradesh                       | 0.0004  | 0.0017  |

Table A7. Normalized decision matrix in MOORA method.

| Normalized Decision Matrix | Maharashtra | Gujarat | Tamil Nadu | Uttar Pradesh | Karnataka | Madhya Pradesh | Andhra Pradesh |
|----------------------------|-------------|---------|------------|---------------|-----------|----------------|---------------|
|                            | 0.5007      | 0.3377  | 0.2762     | 0.4980        | 0.1990    | 0.4607         | 0.2432        |
|                            | 0.3298      | 0.7764  | 0.1056     | 0.1535        | 0.0000    | 0.0000         | 0.5037        |
|                            | 0.0000      | 0.0000  | 0.9785     | 0.0000        | 0.1165    | 0.0000         | 0.1701        |
|                            | 0.4647      | 0.1461  | 0.8100     | 0.1461        | 0.2921    | 0.0000         | 0.0000        |
|                            | 0.4624      | 0.2796  | 0.3105     | 0.0743        | 0.6705    | 0.3150         | 0.2391        |
|                            | 0.2054      | 0.4927  | 0.3832     | 0.1644        | 0.6075    | 0.2162         | 0.3542        |
|                            | 0.3166      | 0.5654  | 0.6218     | 0.0000        | 0.3182    | 0.1591         | 0.2587        |
|                            | 0.6442      | 0.0244  | 0.2545     | 0.5335        | 0.4656    | 0.0313         | 0.1312        |
|                            | 0.5838      | 0.3247  | 0.1604     | 0.2072        | 0.2242    | 0.5596         | 0.3489        |
|                            | 0.3644      | 0.6778  | 0.2713     | 0.0101        | 0.4484    | 0.0841         | 0.3550        |
|                            | 0.1968      | 0.0505  | 0.1513     | 0.1153        | 0.9327    | 0.2053         | 0.1024        |
|                            | −0.3104     | 0.1360  | 0.0906     | 0.4487        | −0.0290   | 0.8214         | 0.0041        |
|                            | 0.1392      | 0.7973  | 0.4139     | 0.1506        | 0.3068    | 0.1206         | 0.2056        |
|                            | 0.4431      | 0.1013  | 0.0731     | 0.4083        | 0.0925    | 0.7743         | 0.1151        |

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