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A MULTI-CRITERIA DECISION-MAKING MODEL TO DETERMINE THE SHARE OF VARIABLE RENEWABLE ENERGY SOURCES

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Abstract

This research study assesses the feasibility of meeting India's forecasted electricity demand of 2030 by generating half of it from renewable sources with minimal cost and greenhouse gas (GHG) emissions. The study examines alternative options for generating the forecasted electricity demand for 2030 using a Multi-Objective Optimization (MOO) approach. Life Cycle GHG emissions and Levelized Cost of Electricity are the input parameters used for optimization. The genetic algorithm in MATLAB is used to examine alternative energy pathways, and the best option is selected using TOPSIS- a Multi-Criteria Decision Making (MCDM) method. The results of the study suggest that the cost-effective and emission-reducing approach to meet the forecasted electricity demand of 2030 is to increase the share of renewable energy sources. Even with the share of renewable energy remaining at the current level of 2022, optimization can reduce costs by 26.5% and emissions by 87% compared to the business-as-usual scenario. Findings of this study have important implications for understanding the feasibility of India's renewable energy target and its potential impact on cost and emission.

Keywords: *Multi-objective optimization, Multi-Criteria Decision Making, Life cycle Emission, Levelized Cost of Electricity, Renewable and Non-Renewable energy*

JEL Codes: *C61, O13, Q42*

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INTRODUCTION

India, as the third-largest global emitter of CO_2, has a significant role to play in addressing ongoing climatic issues. During the period 2012-2021 India’s emission increased by 3.8% per annum and is projected to increase further in the coming years (1). It is mentioned in India's 3rd Biennial Update Report that energy sector contributed 75% to the nation's total emissions. Within the energy sector, electricity production stood out as the dominant contributor, accounting for 53% of the sector's emissions and 40% of the total emissions (2). Consequently, the energy sector has gained particular attention in India's climate actions and the related targets.

India's power sector includes conventional sources like coal, natural gas, oil, hydro, and nuclear energy, along with unconventional sources like wind, solar, and bio-waste. However, India continues to heavily rely on thermal sources, primarily on coal. As of October 2022, fossil fuel sources accounted for approximately 57% of the country's installed electricity generation capacity (3). Nevertheless, India has been actively accelerating its clean energy transition by reducing reliance on fossil fuels and promoting renewable energy sources. As of 2021, India ranked fourth in both wind and solar power capacity, as well as overall renewable power installed capacity (4). India has set an ambitious target to derive 50% of its energy requirement from renewable energy sources by 2030.

India's energy demand has been steadily increasing, more than doubling since 2000. The 29th Electric Power Survey of Central Electricity Authority (CEA) projected India's electricity demand to reach 2,172,304,000 MWh in 2030 (5). It is crucial to meet the growing energy demand, however, the pressing climate issues and India's growing share of global emissions necessitate the identification of pathways to meet the forecasted demand with minimal impact on the climate and the environment. Therefore, the objective of this research paper is to explore alternative options to meet the forecasted electricity demand and the energy target of 2030 at minimum costs and greenhouse gas (GHG) emissions. To achieve this objective, multi-objective optimization method will be employed. Additionally, the paper proposes the use of TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) to determine the best alternative pathway for sustainably meeting India's energy demand and targets.

The paper is organized as follows: Section 2 provides a review of the existing literature. Section 3 describes the methodology. Section 4 presents the empirical findings. Section 5 discusses the results. Finally, Section 6 concludes the paper, summarizing the key findings and providing policy recommendations for India's sustainable energy future.

LITERATURE REVIEW

Several studies have used MOO and MCDM methods to investigate optimal electricity generation options and sustainability considerations in various regions. Adedeji *et. al.* (2020)[6] utilized MOO and TOPSIS methods to analyze electricity generation options in Brunei Darussalam, focusing on cost and emission reduction. They found that optimization of energy mix resulted in reduced emissions and costs compared to the business-as-usual scenario. Lee & Chang (2018)[7] conducted a renewable energy ranking study in Taiwan, highlighting hydro as the top choice, followed by solar PV and wind. Ranganath & Sarkar (2021)[8] assessed the feasibility of solar PV in India, observing a decline in costs. They found that the payback period for investment in solar power plants was less than 30% of the project's life cycle, affirming the economic viability of solar energy in India. Saraswat & Digalwar (2021)[9] evaluated energy source sustainability in India, using integrated fuzzy approach. They highlighted renewable energy sources, particularly solar, wind, and hydro, as the most suitable options for India in terms of sustainability. Atabaki & Aryanpur (2018)[10] developed a sustainable energy plan of 2050 for Iran, recommending a transition towards solar and wind technologies.

They found that by 2050, solar PV gained prominence due to its job prospects and cost-effectiveness.

In addition, Ervural *et. al.* (2018)[11] examined Turkey's energy planning problem, prioritizing renewable energy potential and investment budget. Renewable sources were consistently ranked at the top in all scenario analyses. Mulliner *et. al.* (2016)[12] assessed affordability of sustainable housing in Liverpool. They concluded that no single MCDM method outperforms others and recommended using multiple methods for rational results. Şengül *et. al.* (2015)[13] ranked renewable energy supply systems in Turkey using Fuzzy TOPSIS, with hydropower stations identified as the top-ranked alternative. Wang *et. al.* (2009)[14] reviewed MCDM methods used in sustainable energy aspects. They found that criteria weights significantly influenced MCDM results, with many studies employing equal weights. Finally, Stein (2013)[15] compared electricity production technologies in the USA, highlighting the superiority of renewable sources such as wind and solar PV over non-renewables. They recommended prioritizing solar and wind while reducing reliance on coal, nuclear, and biomass.

Based on the literature reviewed, it is clear that MOO and MCDM methods are commonly used in the energy sector for various purposes. Given India's goals to meet electricity demand, reduce emissions, and address climate change, these methods can help identify the best approach that achieves all objectives simultaneously. This can improve energy planning and resource allocation, leading to a more sustainable energy future for India.

METHODOLOGY

This paper aims to identify the optimal energy source to meet the electricity demand and energy target of 2030. The analysis comprises estimating the units of electricity that would be available in 2030 from alternative energy sources and identifying life cycle GHG emissions and the Levelized Cost of Electricity (LCOE) per unit of electricity produced. Subsequently, these quantitative estimates, along with forecasted electricity demand and energy targets, are used to perform MOO problem to examine alternative energy options. The criteria weights were then identified using Shannon's entropy method. Finally, the TOPSIS, a MCDM method, was employed to identify the best option for meeting the electricity demand and energy target. The research framework of MOO and the MCDM method for identifying the optimal energy mix is illustrated in Fig. 1

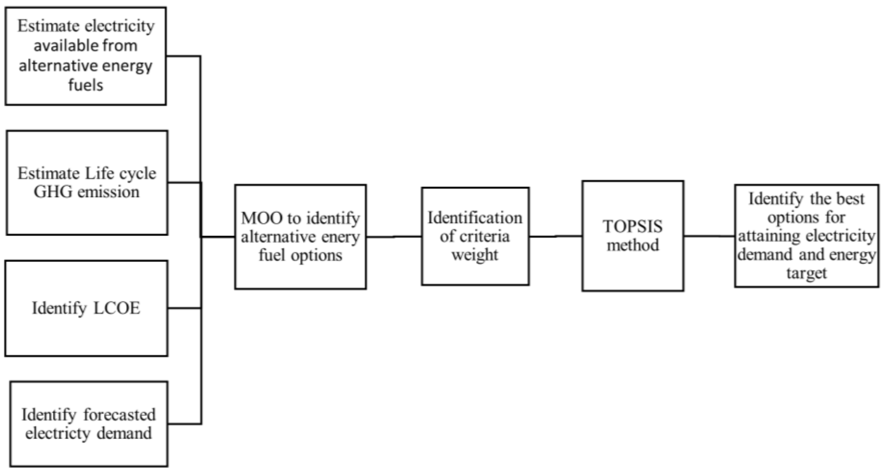

Figure 1: Graph Showing the Research Framework of MOO and MCDM Methods for Identifying Optimal Energy Mix

Electricity Units Available for 2030

India primarily relies on thermal sources to meet its electricity demand. In the fiscal year 2021-22, coal and lignite contributed to 71.47% of the total electricity generation, while gas and nuclear energy accounted for 3.71% and 3.13%, respectively. Renewable energy sources, including wind, solar, biomass, and hydro, collectively contributed to 21.67% of the total electricity generation. Collectively, these seven energy sources represented 99.98% of India's total electricity generation. Considering this, these seven energy fuels were deemed potential sources for meeting the forecasted electricity demand. Therefore, the electricity that would be available in 2030 from each of these seven sources was estimated.

Multi-Objective Optimization (MOO)

MOO refers to a mathematical optimization problem where multiple objective functions need to be optimized simultaneously. In this study, our goal is to meet the projected electricity demand for 2030 while simultaneously minimizing the cost of electricity generation and the associated GHG emissions. Thus, two of our objective functions are to minimize the cost and GHG emissions associated with electricity generation. Additionally, we aim to achieve the energy target set for 2030, which involves maximizing the share of renewable energy (RE) in electricity generation. Hence, we have a total of three objective functions to optimize.

Life Cycle GHG emission Analysis

In order to minimize the GHG emissions resulting from electricity generation, we assessed the life cycle GHG emissions of each of the seven energy sources under consideration. Life cycle GHG emissions refer to the total GHG emissions associated with producing a unit (1 MWh) of electricity, encompassing every stage of its production and usage.

The two main components of life cycle GHG emissions of electricity generation are fugitive emissions and combustion emissions. Fugitive emissions are released during the production, processing, transmission, storage, and distribution of energy fuel, while combustion emissions result from using a particular energy fuel for electricity generation. To estimate fugitive and combustion emissions, yearly activity data (i.e., the quantity of energy fuel used) at each stage of the life cycle is multiplied by the corresponding emission factor (i.e., the amount of GHG generated per ton of fuel). The total GHG emission for a particular fuel is obtained by adding up the fugitive and combustion emissions at each stage. Finally, to calculate the life cycle GHG emissions, the summed value is divided by the electricity generated from that particular fuel. The estimation of life cycle GHG emissions can be expressed mathematically as follows:

$$E = \sum_{k=1}^{n} Q_k \sum_j EF_{kj} \qquad j = x, y, z; k = 1, \dots, n; \tag{1}$$

E = Total GHG emitted by an energy fuel

k indicates different stages in the life cycle of fuel when used in electricity generation

Q_k indicates quantity of fuel at each stage k of the life cycle

j = x, y, z indicates CO_2, N_2O, and CH_4 respectively

EF_{kj} indicates emission factor of the gases x, y, and z in each stage

Levelized Cost of Electricity (LCOE)

Analysis of the second objective involved identification of a variable to indicate cost of electricity production. So, we used LCOE, a metric used to calculate the average cost of building and operating an electricity-generating asset over its lifetime per unit of total electricity generated. It is computed by dividing the net present value of the life cycle cost of the electricity-generating asset by the total electricity generated over its lifetime.

Optimization of the Objective Functions

A multi-objective linear programming (MOLP) model is formulated to optimize each of the objective functions. The developed model can be expressed as follows;

$$\min Z1 = aX_1 + bX_2 + cX_3 + dX_4 + eX_5 + fX_6 + gX_7 \tag{2}$$

$$\min Z2 = aY_1 + bY_2 + cY_3 + dY_4 + eY_5 + fY_6 + gY_7 \tag{3}$$

$$\max Z3 = (d+e+f+g)100/ ef \tag{4}$$

Subject to the constraints;

$$a+b+c+d+e+f+g \geq ef \tag{5}$$

$$0 \leq a \leq a_m \tag{6}$$

$$0 \leq b \leq b_m \tag{7}$$

$0 \le c \le c_m$ (8)

$0 \le d \le d_m$ (9)

$0 \le e \le e_m$ (10)

$0 \le f \le f_m$ (11)

$0 \le g \le g_m$ (12)

Z1, Z2, Z3 are the objective functions to be optimized
X represents levelized cost of electricity
Y shows life cycle GHG emission
ef denoted the forecasted electricity demand
a, b,....,g is the electricity to be generated from coal, natural gas, nuclear, hydro, wind, solar, and biomass energy sources.
a, b,.....,g subscripted with m indicates the maximum quantity of electricity available in 2030 from each of the seven energy sources.

Multi-Criteria Decision-Making (MCDM) Method

In multi-objective optimization, unlike a single objective optimization problem, it is not possible to get a single solution that optimizes all objective functions simultaneously. Instead, a set of equally good solutions are generated, in which none of the objective function can be improved without deteriorating some other objective functions. In the present study, the optimization problem provides alternative solutions for meeting the electricity demand and achieving the energy target. Manual selection among these alternatives is impossible due to conflicting criteria; some may offer lower costs but higher emissions, while others reduce emissions at potentially higher costs.

To address this, the study employs MCDM method. MCDM is used for selecting the best option from a set of alternatives constrained by conflicting criteria. Here, the choice between fossil fuels and renewable energy (RE) sources presents such conflicts. While fossil fuels offer lower costs, they lead to higher emissions. Conversely, RE sources reduce emissions but may entail higher costs due to infrastructure constraints.

To navigate these trade-offs TOPSIS, a classic MCDM method, is chosen to select the best solution from the optimization-generated alternatives.

TOPSIS Method

This method was proposed by Hwang & Yoon (1981). The idea of the method is that the chosen alternative should have the shortest distance from the ideal solution and the farthest from the anti-ideal solution. Steps involved in TOPSIS is showed in Fig.2, and explained in the following session

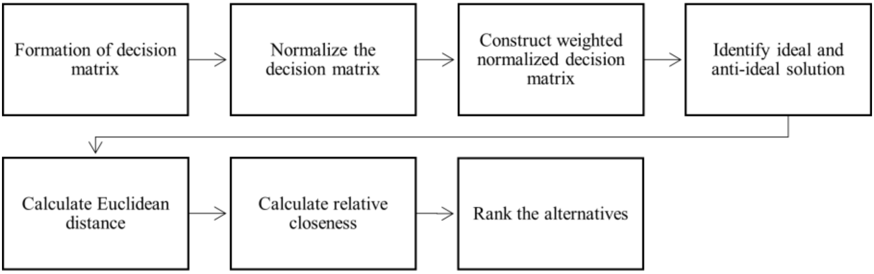

Figure 2: Steps Involved in TOPSIS Method

Step 1: Formation of Decision matrix

An MCDM problem with m alternatives (A_1, A_2… A_m) and n criteria (C_1, C_2, ..., C_n) can be expressed in a matrix format as follows;

$$\begin{array}{cc} & C_j \\ A_i = & \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix} = [aij]_{m\times n} \end{array}$$

Here A represents the alternative and C the criteria. The elements aij denote the attribute of i^{th} alternative under j^{th} criterion.

Step 2: Normalize the decision matrix

Attributes of the decision matrix have to be converted to common comparable units by normalizing the matrix.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, i = 1,2, \dots \dots, m; j = 1,2, \dots \dots, n \tag{13}$$

Step 3: construct the weighted normalized decision matrix

Calculate the weighted normalized decision matrix by multiplying the attribute of the normalized decision matrix by the weight of the corresponding criteria. This study assessed criteria weight using Shannon's entropy weight calculation method[1].

$$V_{ij} = w_j r_{ij}, \quad \sum_{j=1}^{n} w_j = 1 \tag{14}$$

Here w_j is the weight of j^{th} criteria.

Step 4: Identify ideal and anti-ideal solution

From the set of alternatives, the ideal and anti-ideal solution denoted as A^+ and A^- respectively has to be identified as follows;

$$A^+ = \{(\max v_{ij} \mid j \epsilon J) \ or \ (\min v_{ij} \mid j \epsilon J')\}, i = 1,2, \dots . m$$
$$= \{v_1^+, v_2^+, \dots ., v_n^+\} \tag{15}$$
$$A^- = \{(\min v_{ij} \mid j \epsilon J) \ or \ (\max v_{ij} \mid j \epsilon J')\}, i = 1,2, \dots . m$$
$$= \{v_1^-, v_2^-, \dots ., v_n^-\} \tag{16}$$

Where J and J' are sets of benefit and cost criteria respectively.

If the criterion is benefit, then the ideal solution will be the highest value among the available alternative solutions, whereas for the cost criteria, it will be the minimum value. Conversely, the minimum value among the benefit criteria and the maximum value among the cost criteria form the anti-ideal solution.

Step 5: calculate Euclidean distance

Euclidean distance of each attribute from the ideal and anti-ideal solutions has to be identified. Euclidean distance from the ideal solution is specified as;

[1] This method is explained in the section 3.3.2

$$S_i^+ = \sqrt{\sum_{i=1}^{n} \left(v_{ij} - v_j^*\right)^2}, i = 1,2, \dots\dots, m \tag{17}$$

Here $\left(v_{ij} - v_j^*\right)^2$ is the square of the distance of attribute under each criterion from the ideal solution. This distance of each attribute has summed up and taken its square root to obtain the Euclidean distance. In a similar way, Euclidean distance from the anti-ideal solution has also been calculated as shown below below;

$$S_i^- = \sqrt{\sum_{i=1}^{n} \left(v_{ij} - v_j^-\right)^2}, i = 1,2, \dots\dots, m \tag{18}$$

Step 6: calculate relative closeness

Relative closeness of each of the attributes to the ideal solution is assessed as show below.

$$C_i^* = \frac{S_i^-}{S_i^* + S_i^-}, 0 < C_i^* < 1, i = 1,2, \dots\dots, m \tag{19}$$

If relative closeness is closer to 1, it indicates that the alternative solution is closer to the ideal solution. Hence best alternative will have higher values for C_i^*.

Step 6: *Ranking of alternatives*

Rank the alternatives based on their relative closeness. Alternatives with higher relative closeness will be ranked at the top.

Criteria Weight Calculation

Weights for different criteria can be assigned using subjective or objective methods. Subjective weights rely on expert opinions, while objective weights are calculated based on the estimated alternatives and their performance with respect to each criterion. Objective weights can avoid the subjective bias of decision-makers, thereby enhancing the objectivity of the decision-making process (7). The present study utilized an objective method called Shannon's entropy weight calculation, the calculation method of which is explained below.

Top of Form

Step 1: formation of decision matrix

The decision matrix for alternatives and criteria is the same as the one shown under the TOPSIS method, hence, it is not reiterated here.

Step 2: Normalize the decision matrix to render attribute dimensions non-dimensional for comparison.

$$r_{ij} = \frac{a_{ij}}{\sum_{i=1}^{m} a_{ij}}, \text{ i= 1, 2,....., m} \tag{20}$$

Step 3: Compute entropy

$$e_j = -K \sum_{i=1}^{m} r_{ij} ln r_{ij}, j = 1, 2, \ldots., n \tag{21}$$

Where *K = 1/ ln m*

Step 4: Calculate the weights of each criterion as follows

$$w_j = \frac{1-e_j}{\sum_{i=1}^{n} 1-e_j}, j = 1, 2, \ldots., n \tag{22}$$

EMPIRICAL ANALYSIS

To estimate the electricity resources that would be generated in 2030 from the energy sources considered in this study, we assume that the installed electricity generation capacity and capacity utilization factor (measured with the Plant Load Factor - PLF) will remain consistent with the current situation as of June 2022. Data on installed capacity were collected from the Ministry of Power[16]. Data on the capacity utilization factor for coal, natural gas, hydro, wind, and solar were obtained from MNRE[17], for nuclear and biomass, we relied on All India Electricity Statistics and estimates from the Center for Science and Environment, respectively[18,19]. The estimated units of electricity available in 2030 are presented in Table 1. Installed capacity and capacity utilization factor of each power plants in 2022 is shown in column 2 and 3 respectively. Units of electricity that would be generated in 2020 if the existing power plant works at the given capacity utilization factor for 24 hours*365 days is shown in column 4.

Table 1: Electricity resources available in 2030

Energy sources	Installed capacity (MW) in 2022	Capacity factor (%)	Maximum availability in 2030 (installed capacity *capacity factor*8760)
Coal & lignite	210700	60	1107439200
Natural Gas	24856	23	50079868.8
Nuclear	6780	64	38011392
Hydropower	46850	60	246243600
wind (land & offshore)	40788	35	125056008
solar PV	57706	22	111211003.2
Biomass	10206	17	15198775.2

Life Cycle GHG Emission Estimates

Growing energy demand amidst climate change underscores the need of a discussion on energy sector. Numerous studies have utilized life cycle approach to evaluate emissions from power generation. This study adopts a similar approach to estimate GHG emissions (carbon dioxide, nitrous oxide, and methane) from coal and natural gas-based power plants.

GHG Emission from Coal Power Plants

GHG emission from any power plant consist of fugitive and combustion emission.

Fugitive emission from coal plants

Coal mining industry in India employs both underground and open-cast mining methods, hence to get a complete picture of GHG, emission from mining and post-mining activities of these two methods have to estimated. Activity data of coal production used in the estimation process was of the financial year 2018-19 and is collected from the Coal Directory of India [20]. Emission factor (country-specific) used are from the existing literature[21]. To estimate emission from underground mines an equal weight of 0.33 is given to each of the three categories of coal seams[2]. The estimated methane emissions were converted to CO_2-equivalent using the Global Warming Potential (GWP) value provided by IPCC in its 5th assessment report. The emissions from underground and opencast mines were combined to determine the total fugitive emissions from coal power plants. In 2018-19, 76.16% of the total coal produced in India was used in electricity generation, hence this ratio is used to estimate the portion of fugitive emissions to which electricity generation is responsible for.

Combustion emission from coal

In addition to coal, all other fuels used must be considered when estimating combustion emissions from coal plants. Therefore, activity data for various fuels was obtained from the All India Electricity statistics. The Net Calorific Value (NCV) and emission factor were sourced from Nazar et al[21]. To calculate the amount of N_2O, CH_4, and CO_2 emitted during the combustion process, the activity data of each fuel is multiplied by the NCV and emission factor. N_2O, and CH_4 emissions are then converted to CO_2 -equivalent using their respective GWP values. Finally, emissions from each fuel are aggregated to obtain the total combustion emissions from coal power plants. To determine the total GHG emissions from coal power plants, the combustion emissions obtained here are added to the fugitive emissions calculated earlier.

Life cycle GHG (LCGHG) emission from coal

Value of GHG emission estimated above is divided by annual electricity generated from coal power plants to find out the life cycle GHG emission of coal.

[2] emission factors are available for three categories of coal seems but only a combined figure is available for activity data

GHG Emission from Natural Gas Power Plants

Here also total emission is composed of fugitive and combustion emission.

Fugitive emission from natural gas

Emissions from the production, processing, flaring, leakage, and distribution of natural gas is considered for estimation. To estimate these emissions, activity data (considering domestically produced and imported gas) is obtained from the Indian Petroleum & Natural Gas Statistics 2020-21, and emission factor from Nazer et al[21]. Methane being the major GHG emitted by gas plants its value is estimated using equation 1 and converted to CO_2-equivalent using GWP value. In 2018-19, 21.93% of the total natural gas available was used by power utilities. Hence this ratio is used to determine the portion of fugitive emissions for which electricity generation is responsible for.

Combustion emission from natural gas

Activity data of fuel consumption by natural gas power plants is obtained from All India Electricity Statistics[18], while the NCV and emission factors used are from Nazar et al[21]. The amount of CO_2, N_2O, and CH_4 emitted by each fuel is estimated, and N_2O and CH_4 are converted to CO_2-eq using their respective GWP values. The combined values these gases for each fuel were then added to obtain the total combustion emission from natural gas power plants. Finally, total GHG emissions were calculated by adding fugitive and combustion emissions together.

Life cycle GHG (LCGHG) emission from natural gas

Total GHG emission estimate is divided by the annual electricity generation from gas plants to obtain its life cycle GHG emission measured in tons of CO_2-equi/GWh.

Life cycle GHG emission from nuclear and renewable energy

Regarding the LCGHG emission of renewable (hydro, wind, solar, and biomass) and nuclear energy sources this study used the estimates provided by the National Renewable Energy Laboratory (NREL)[22]. NREL made a review and harmonization of existing estimates on life cycle assessments (LCAs) of electricity generation to reduce uncertainty and increase the credibility of the estimates. Therefore, the figures provided by NREL can be considered robust for the life cycle emissions of renewable and nuclear electricity generation.

Levelized Cost of Electricity

Table 2: LCGHG and LCOE of Seven Energy Sources

Energy sources for meeting 2030 electricity demand	LCGHG (kg/MWh)[3]	LCOE (USD/MWh)
Coal/lignite	2264.55	94.61
GAS	602.22	81
Nuclear	13	48.17
hydropower (comprising	21	28.09
wind (land & offshore)	13	25.43
solar PV	43	25.38
Biomass	52	113.59

The large number of power plants for each energy fuel in India is a challenge for obtaining sufficient plant-level data to conduct life cycle analysis. Additionally, there can be significant variations in the cost of electricity generation between different plants. To address this, we used India-specific estimates of LCOE provided by the International Energy Agency (IEA). These estimates are of the power plants to be commissioned by 2025. However, as there is no estimates for gas power plants in IEA's analysis, we used the estimated global benchmark LCOE of natural gas provided by BloombergNEF [23]. Estimates of the LCGHG and LCOE of the seven energy sources are presented in Table 2.

[3] Tons/GWh is same as kg/MWh

Optimization Analysis

Multi-Objective Linear Programming (MOLP) model is used to explore alternative options for meeting the forecasted electricity demand of 2030. Optimization is performed using the function *gamultiobj* in MATLAB R2022a version. Different scenarios constrained by the share of RE in electricity generation were considered for optimization. The specific scenarios and their optimization problem are formulated as follows:

Business as Usual (BAU) Scenario

In this scenario, no optimization is performed, and it is assumed that the installed capacity of electricity generation will remain same as that in 2022. Hence the electricity consumed from all the sources except coal is the maximum available (as showed in Table 2). Since coal has been the main source for electricity generation in India, the remaining portion of the projected demand would be met by producing more units of electricity from coal. The proportion of 2030 electricity demand that would be met with each energy source, along with the resulting cost and emissions, are presented in Table 3.

Table 3: Allocation of Forecasted Electricity Demand and Associated Costs And Emissions for 2030 in BAU Scenario

Electricity resource	Proportion of 2030 demand	Electricity Generation Cost (USD/Mwh)	Total GHG emission (kg/Mwh)
Coal	1586503353		
Natural gas	50079868.8		
Nuclear	38011392		
Wind (land & offshore)	246243600	170632681477.47	3635738667419.98
Solar PV	125056008		
Hydropower	111211003.2		
Biomass	15198775.2		

It is clear that if India continues with BAU scenario, meeting the projected electricity demand of 2030 would result in a cost of 170.633

billion US dollars and in an emission of 3.635 billion tons of CO_2 equivalent.

Optimization Scenario 1

Here the objective is to meet the electricity demand of 2030 at minimum generation cost and emission. No improvement in renewable energy facilities is assumed i.e. as in BAU scenario renewable energy sources will contribute around 23% to the forecasted demand. Remaining demand will be met from fossil fuels at the minimum cost and emission. Multi-objective optimization is performed using the following fuzzy.

Min Cost = a94.61+b81+c48.17+d28.09+e25.43+f25.38+g113.59

Min GHG = a2264.55+b602.22+c13+d21+e13+f43+g52

Max RE = (d+e+f+g)*100)/2172304000)

Subject to the constraints;

a+b+c+d+e+f+g = 2172304000

(d+e+f+g*100)/2172304000) = 22.9

Bounds are;

0 <= a, b, c, d, e, f, g

(a=coal, b=natural gas, c=nuclear, d=hydro, e=wind, f=solar, and g=biomass)

The alternative options obtained for this scenario are presented in Table 4. Comparing this outcome with that of the BAU scenario, it is evident that the 2030 demand can be met with lower cost and emissions. Forecasted demand can be met at a reduced cost of 125.31 billion US dollars and at a lower emission of .47 billion tons of CO2-eq, representing a decrease of 26.5% and 87% in cost and emissions.

Table 4: Alternative Options for Optimization Scenario 1

No	cost (10^6)	ghg (10^6)	RE (%)	Coal	Gas	Nuclear	Hydro	Wind	solar	biomass
1	125312.5489	468165.6	22.8998	119179657.5	272068843.3	1283602333	231746040.4	9089179.9	64866294.5	15198774.8
2	125313.0946	467404.5	22.89966	119529458.9	269405329.9	1285918990	231272432.8	8992108.4	64606850.7	15198774.8
3	125313.2413	467200	22.89962	119623440.1	268689724.2	1286541406	231145188.2	8966028.5	64537145.5	15198775
4	125313.4287	466938.7	22.89958	119743532.7	267775300.9	1287336748	230982591.5	8932702.5	64448074.6	15198775.1
5	125313.5782	466730.1	22.89954	119839387.9	267045419.2	1287971582	230852808.7	8906102.2	64376979.1	15198774.6
6	125313.7149	466539.5	22.89951	119926989.2	266378396.7	1288551741	230734203.7	8881792.9	64312006.8	15198774.9
7	125313.7429	466500.3	22.8995	119944998.7	266241260.2	1288671019	230709818.2	8876796	64298649.2	15198774.9
8	125313.93	466239.4	22.89945	120064938.4	265327994	1289465354	230547429.1	8843511.6	64209690.9	15198775.1
9	125314.2908	465736.3	22.89936	120296151.8	263567453.9	1290996629	230234379.7	8779350.1	64038202.7	15198775
10	125314.4675	465489.8	22.89932	120409433.8	262704883.6	1291746871	230081003.2	8747914.1	63954182.7	15198775.2
11	125314.5784	465335.1	22.89929	120480543.5	262163427.6	1292217815	229984725.8	8728180.9	63901441.2	15198774.7
12	125314.6339	465257.7	22.89928	120516091.9	261892748.1	1292453245	229936597.4	8718315.2	63875075.1	15198775.2

Optimization Scenario 2

This scenario presents a case of expansion in RE facility. The share of RE in forecasted electricity demand will increase beyond the 22.9% (case that is considered in optimization scenario 1). However, we impose an additional constraint that limits RE share to a maximum of 50% of the electricity demand. The fuzzy used in the optimization problem is as follows:

Min Cost = a94.61+b81+c48.17+d28.09+e25.43+f25.38+g113.59
Min GHG = a2264.55+b602.22+c13+d21+e13+f43+g52
Max RE = (d+e+f+g)*100)/2172304000)
Subject to the constraints;
a+b+c+d+e+f+g= 2172304000
22.9 <= (d+e+f+g)*100)/2172304000) <= 50 Bounds;
0 <= a, b, c, d, e, f, g

Alternative options obtained for this scenario are presented in Table 5. Comparing this outcome with that of optimization scenario reveals that expansion of RE will leads to cost and emissions reductions. Both cost and emissions decrease as the RE share grows, until it reaches at 41% of forecasted demand, with cost continuing to decrease until it reaches 43.9%. However, further expansion beyond 44% results in higher costs and emissions. This could be attributed to the inclusion of biomass alongside other RE technologies[4]. Nevertheless, in comparison to BAU scenario, present scenario could attain significant reductions in cost and emissions. Expanding the RE facility to contribute 35% allows meeting forecasted demand at a cost of US$105.2 billion and emissions of 0.14 billion tons of CO2-eq, marking decreases of 38.4% in cost and 96% in emissions. Even with RE contribution expanding to 49.1% of demand, a decline of 15.8% in cost and 65.7% in emissions is achievable.

[4] With respect to the cost and emission considered in this study biomass has the highest cost of electricity production and its GHG is highest among the RE sources.

Table 5: Alternative Options for Optimization Scenario 2

No	cost (10^6)	ghg (10^6)	RE (%)	Coal	Gas	Nuclear	hydro	Wind	Solar	Bio mass
1	105199.91	142533.57	35.40	7934525.32	134965865.42	1260420936.72	172426887.57	122642277.12	328665523.26	145247984.58
2	111608.32	280418.70	41.30	68310908.63	145149151.30	1061753856.99	278913156.71	327878616.42	78267152.00	212031157.94
3	117168.17	455821.98	42.05	139023184.27	168225049.38	951678969.75	299843759.47	248587098.22	132091696.33	232854242.59
4	122567.66	619467.08	43.30	205494346.96	188924881.80	837296690.17	328753528.34	202495594.55	151803886.86	257535071.32
5	125036.71	691824.00	43.94	234980397.89	197864082.08	785027400.38	343943033.39	185530474.34	155163711.51	269794900.42
6	127021.37	750538.43	44.53	258958032.63	205087453.82	740887588.69	356620150.91	176502065.41	154307981.48	279940727.06
7	130315.99	846677.53	45.14	297960488.85	217137013.69	676695535.94	374836673.60	140063392.89	170482860.75	295128034.29
8	143624.47	1245931.04	49.10	460866930.47	266658247.88	378145806.87	456505350.74	76811163.04	171734705.34	361581795.66
9	143624.47	1245931.04	49.10	460866930.24	266658247.65	378145806.63	456505351.57	76811159.82	171734706.16	361581797.93

Optimization Scenario 3

Objective of this scenario is to meet the electricity demand along with the energy target of 2030. That is to make RE contributing 50% to the forecasted demand. The fuzzy used in the optimization problem is specified as follows:

Min Cost = a94.61+b81+c48.17+d28.09+e25.43+f25.38+g113.59

Min GHG = a2264.55+b602.22+c13+d21+e13+f43+g52

Max RE = (d+e+f+g)*100)/2172304000)

Subject to the constraints;

a+b+c+d+e+f+g= 2172304000

(d+e+f+g*100)/2172304000) = 50 Bounds; 0 <= a, b, c, d, e, f, g

The alternative options of this scenario are shown in Table 6. When comparing this outcome with that of BAU scenario it is clear that forecasted demand and the energy target of 2030 could be attained at a lower cost and emission. Out of these 10 alternative option declines of 20.3% in cost and 86.6% in emissions is achievable in first alternative compared to the BAU scenario.

Table 6: Alternative Options for Optimization Scenario 3

No	cost (10^6)	ghg (10^6)	re (%)	coal	Gas	Nuclear	Hydro	wind	solar	biomass
1	135967.262	485175.1607	50	48506621.72	548414959.31	489211233.43	395036696.39	95221993.58	201979851.8	393932643.8
2	135967.2621	485175.1606	50	48506621.71	548414959.30	489211234.17	395036696.63	95221993.32	201979851.1	393932643.8
3	135967.2621	485175.16	50	48506621.47	548414959.06	489211234.18	395036696.14	95221994.08	201979850.5	393932644.6
4	136019.8749	487216.6777	50	49011305.87	549974909.42	487146475.77	395939819.6	94941891.12	201634343.2	393655255
5	136064.3761	488943.4411	50	49438179.37	551294353.43	485400053.46	396703703.04	94704973.73	201342104.4	393420632.6
6	136145.9774	492109.7817	50	50220931.26	553713797.26	482197665.24	398104424.58	94270541.43	200806230	392990410.2
7	136187.6935	493728.4805	50	50621090.19	554950667.16	480560538.09	398820502.33	94048451.41	200532280.6	392770470.2
8	136259.5594	496517.0632	50	51310456.50	557081460.83	477740208.10	400054111.76	93665848.6	200060339.5	392391574.7
9	136353.8191	500174.5914	50	52214635.08	559876227.67	474041040.76	401672124.11	93164024.93	199441336.81	391894610.64
10	136353.8193	500174.591	50	52214634.90	559876227.50	474041040.58	401672123.93	93164023.97	199441335.1	391894614

Choice of Best Solution using TOPSIS Method

TOPSIS an MCDM method is used to select the best option among the alternatives obtained from the three scenarios. Prior to TOPSIS, Shannon's entropy method is used to determine the criteria weight. Weights obtained for the three criteria (i.e., objective functions) of this study are shown in Table 7. GHG emissions received the highest weight, followed by the share of RE in electricity generation. The cost factor was given the least importance. This suggests that it is essential for India to minimize GHG emissions while planning for long-term electricity demand.

Table 7: Criteria Weights Obtained From Shannon's Entropy Method

Criteria	Weight
LCOE	0.016749
LCGHG	0.551459
RE share	0.431792

Optimization of the three scenarios resulted in 31 alternative options, which were subsequently organized into a decision matrix. Then it was normalized using Equation 13. Criteria weight, obtained from Shannon's entropy method, were applied to construct weighted normalized decision matrix. By employing Equations 15 and 16, the ideal and anti-ideal solutions were identified. Subsequently, Equations 17 and 18 were used to calculate the distance of each alternative from the ideal and anti-ideal solutions, denoted as S_i^+ and S_i^-, respectively. The relative closeness of each alternative was determined using Equation 19, denoted as C_i^*. Finally, all 31 alternatives were ranked based on their relative closeness values. The alternative with the highest relative closeness represents the best option to meet the forecasted electricity demand and energy targets. Result obtained from this TOPSIS analysis is presented in Table 8. The table shows 31 alternative solutions with their values of the objective functions, distances from the ideal and anti-ideal solutions, relative closeness, and ranking.

Table 8: Result of TOPSIS Analysis with Shannon's Entropy Weight

Criteria	cost (10^6)	ghg (10^6)	re (%)	S_i^+	S_i^-	C_i^*	Rank
21	105199.911	142533.5719	35.4	0.028577	0.188657259	0.86844898	1
16	111608.3229	280418.6962	41.3	0.028926	0.167598717	0.852814229	2
13	117168.1702	455821.9826	42.0	0.055349	0.13908966	0.715340043	3
27	135967.2621	485175.16	50.0	0.058094	0.13944734	0.705913241	4
30	135967.2621	485175.1606	50.0	0.058094	0.13944734	0.705913241	5
25	135967.262	485175.1607	50.0	0.058094	0.13944734	0.705913241	6
23	136019.8749	487216.6777	50.0	0.058441	0.139127287	0.704200212	7
28	136064.3761	488943.4411	50.0	0.058733	0.138856675	0.702751791	8
26	136145.9774	492109.7817	50.0	0.05927	0.138360694	0.70009704	9
29	136187.6935	493728.4805	50.0	0.059544	0.138107256	0.698740479	10
31	136259.5594	496517.0632	50.0	0.060017	0.137670839	0.696404454	11
24	136353.8193	500174.591	50.0	0.060637	0.137098797	0.693342371	12
22	136353.8191	500174.5914	50.0	0.060637	0.137098797	0.693342371	13
4	125314.6339	465257.7139	22.9	0.076188	0.132352694	0.634659979	14
8	125314.5784	465335.0624	22.9	0.076198	0.132339581	0.634608344	15
1	125314.4675	465489.7865	22.9	0.076217	0.13231335	0.634505041	16
11	125314.2908	465736.2704	22.9	0.076247	0.132271562	0.63434043	17
6	125313.93	466239.3531	22.9	0.076308	0.132186272	0.634004293	18
12	125313.7429	466500.324	22.9	0.07634	0.132142029	0.633829838	19
7	125313.7149	466539.5132	22.9	0.076345	0.132135385	0.633803636	20
2	125313.5782	466730.1167	22.9	0.076368	0.132103071	0.633676177	21
9	125313.4287	466938.6858	22.9	0.076393	0.132067711	0.633536669	22
3	125313.2413	467199.9854	22.9	0.076425	0.132023412	0.633361838	23
10	125313.0946	467404.4729	22.9	0.07645	0.131988744	0.633224978	24
5	125312.5489	468165.5852	22.9	0.076543	0.131859709	0.632715266	25
20	122567.6581	619467.0804	43.3	0.081915	0.113457105	0.580722494	26
18	125036.7135	691823.998	43.9	0.093879	0.102558819	0.522093485	27
19	127021.3697	750538.4289	44.5	0.103634	0.094044899	0.475745742	28
15	130315.9866	846677.5344	45.1	0.119758	0.080460154	0.401862546	29
17	143624.4682	1245931.036	49.1	0.187076	0.051257651	0.215067052	30
14	143624.4681	1245931.036	49.1	0.187076	0.051257651	0.215067051	31

Sensitivity Analysis

Some previous studies[6,7] have highlighted that the preference ranking through TOPSIS method is highly sensitive to the criteria weight. Hence to assess the influence of criteria weights on the ranking, another round of TOPSIS analysis was conducted by assigning an equal weight of 0.33 to each of the three criteria. Output of this sensitive analysis is presented in Table 9.

Table 9: Result of TOPSIS Analysis with Equal Weight

Criteria	cost (10^6)	ghg (10^6)	Re (%)	S_i^+	S_i^-	C_i^*	Rank
16	111608.3229	280418.6962	41.3	0.01933545	0.102798	0.841686	1
21	105199.911	142533.5719	35.4	0.021840502	0.114854	0.840225	2
13	117168.1702	455821.9826	42.0	0.034380297	0.085978	0.714351	3
27	135967.2621	485175.16	50.0	0.037525355	0.087241	0.699235	4
25	135967.262	485175.1607	50.0	0.037525355	0.087241	0.699235	5
30	135967.2621	485175.1606	50.0	0.037525355	0.087241	0.699235	6
23	136019.8749	487216.6777	50.0	0.037726363	0.087057	0.697665	7
28	136064.3761	488943.4411	50.0	0.037896444	0.086901	0.696337	8
26	136145.9774	492109.7817	50.0	0.038208466	0.086616	0.693903	9
29	136187.6935	493728.4805	50.0	0.038368052	0.08647	0.692658	10
31	136259.5594	496517.0632	50.0	0.038643088	0.086219	0.690515	11
24	136353.8193	500174.591	50.0	0.039004041	0.085891	0.687705	12
22	136353.8191	500174.5914	50.0	0.039004041	0.085891	0.687705	13
4	125314.6339	465257.7139	22.9	0.052907337	0.079647	0.600862	14
8	125314.5784	465335.0624	22.9	0.052912189	0.079639	0.600816	15
1	125314.4675	465489.7865	22.9	0.052921897	0.079623	0.600725	16
11	125314.2908	465736.2704	22.9	0.052937368	0.079598	0.60058	17
6	125313.93	466239.3531	22.9	0.052968968	0.079548	0.600284	18
12	125313.7429	466500.324	22.9	0.052985372	0.079521	0.60013	19
7	125313.7149	466539.5132	22.9	0.052987836	0.079517	0.600107	20
2	125313.5782	466730.1167	22.9	0.052999824	0.079498	0.599995	21
9	125313.4287	466938.6858	22.9	0.053012945	0.079477	0.599872	22
3	125313.2413	467199.9854	22.9	0.053029392	0.079451	0.599718	23
10	125313.0946	467404.4729	22.9	0.053042269	0.07943	0.599597	24
5	125312.5489	468165.5852	22.9	0.05309024	0.079353	0.599148	25
20	122567.6581	619467.0804	43.3	0.050053489	0.071154	0.587043	26
18	125036.7135	691823.998	43.9	0.057190943	0.064978	0.531868	27
19	127021.3697	750538.4289	44.5	0.063025885	0.060249	0.488737	28
15	130315.9866	846677.5344	45.1	0.07272764	0.052756	0.420422	29
17	143624.4682	1245931.036	49.1	0.113333411	0.039174	0.256866	30
14	143624.4681	1245931.036	49.1	0.113333411	0.039174	0.256866	31

Shannon's entropy method provided highest weightage to GHG emission and the lowest to the cost of production. As a result, TOPSIS with shannon's criteria weight ranked solution with the lowest GHG emission at the top, it results in cost of US$ 105.19 billion and GHG emission of .142 billion tons. Whereas TOPSIS with equal weightage ranked a solution that results in cost of US$ 111. 6 billion and emission of .28 billion tons at the top. Therefore, it can be concluded that the ranking in TOPSIS to some extend is influenced by the criteria weights.

DISCUSSIONS OF THE EMPIRICAL ANALYSIS

Analysis of alternate scenarios indicates that if India continues to be in BAU scenario, with respect to electricity generation and is not choosing optimal energy mix, it would incur a cost of 170.632 billion US dollars to generate the forecasted electricity demand of 2030. This would also result in the emission of 3.635 billion tons of CO_2 equivalent. Output of one of the optimization scenarios showed that even if India doesn't expand its renewable energy capacity choice of optimal energy mix could meet the demand at a lower cost of US $125.31 billion and lower emission of .47 billion tons of CO_2 equivalent. This indicates that optimizing the energy mix alone can reduce the emission and cost significantly.

The other two scenarios of this study, scenario that analyzed the case of renewable energy expansion until it reaches to 50% of electricity demand, and the scenario meant to attain the energy target of 2030, also showed that forecasted electricity demand can be attained at a lower cost and emission as compared to BAU scenario.

The TOPSIS method used to identify the best options for meeting the forecasted electricity demand ranked options from the scenario with RE expansion (from 22.9% to 50%) at the top. Second ranked alternatives are from the scenario that meet the energy target of 2030. This ranking means that if India's aim is to meet the forecasted demand of 2030 it can be attained at lower cost but to increase the share of RE to 50% India has to incur some extra cost. However, comparison of the scenario attaining 2030 target with BAU scenario showed that expansion of renewable to 50% of the electricity demand could reduce the cost of electricity production by 20% and GHG emission by 86%.

In TOPSIS ranking some solutions from the scenario that maximizes RE from 22.9% to 50% was ranked at the bottom. This means that increasing the share of RE without choosing the optimal energy mix will not reduce the overall cost and emission. Hence alternative energy mix have to be examined and the best have to be chosen for meeting the electricity demand at minimum cost and emission.

Overall, the empirical findings consistently demonstrate that RE expansion could reduce both the cost and the emission. This highlights the significance of RE as the most viable source for meeting electricity demand at minimum cost and environmental impact. However, when considering a massive acceleration of RE it is crucial to consider various other aspects such as resource availability, infrastructure requirements, potential impacts on stakeholders, and others.

Furthermore, it is important to note that the results of the TOPSIS analysis to some extents are sensitive to the chosen criteria weights. These weights can influence the relative rankings of the alternatives. Therefore, it is essential to carefully consider and assign appropriate weights to the criteria to ensure accurate and robust decision-making.

CONCLUSION

The application of multi-objective optimization and TOPSIS in the energy sector has proven to be highly valuable for policymakers. It facilitates effective energy planning, efficient allocation of energy resources, and optimal selection of energy portfolios, among other benefits. When applied in the Indian context, this method reveals that a significant transition to renewable energy would enable India to meet its growing energy demand while minimizing the impact on climate and the environment. Such a transition not only yields environmental advantages but also reduces the cost of electricity generation due to the advantage that renewable energy has in the form of technological advancements, economies of scale, and improved financial options.

Comparing the results of multi-objective optimization for different scenarios, it becomes evident that the cost of electricity generation and greenhouse gas emissions in scenarios with optimal energy mix and with renewable energy expansion is lower than that in the business-as-usual scenario. This signifies that instead of continuing with the current energy portfolio, selecting an optimal portfolio with increased share of renewable energy would enable India to meet the projected demand at a lower cost and emission. Therefore, it is recommended for India to identify the optimal energy portfolio to address its growing energy demand. However, achieving energy-related targets and facilitating a substantial transition to renewables requires the adoption of appropriate measures to tackle the challenges associated with renewable energy, considering factors such as high upfront costs, infrastructure development, regulatory frameworks, and storage solutions.

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