Available online at www.sciencedirect.com

ScienceDirect

Energy Reports 8 (2022) 605–614

www.elsevier.com/locate/egyr

2022 International Conference on Energy Storage Technology and Power Systems (ESPS 2022), February 25–27, 2022, Guilin, China

An application of dimensional reduction approach for evaluating energy generation alternatives for energy sustainability

Aamir Mehmood[a], Misbah Iqbal[a], Long Zhang[b], Huijuan Xiao[a], Jingzheng Ren[a,*]

[a] *Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hong Kong SAR, China*
[b] *School of Business, Xinyang Normal University, Xinyang 464000, China*

Received 19 September 2022; accepted 29 September 2022
Available online 17 October 2022

Abstract

The success of sustainability is mainly linked to the energy sector, which is governed by the mix of different fuel resources. This work aims to calculate the sustainability performance scores (SPSs) of the energy alternatives that constitute Pakistan's current electric energy mix and future energy plans. For this purpose, a decision framework consisting of eighteen indicators is considered for evaluating the performance of energy alternatives. The SPSs of energy alternatives are calculated using the dimensional reduction feature of the principal component analysis technique. The resultant prioritization of energy alternatives favors solar resource the most for planning a roadmap for sustainable net-zero energy infrastructure development. Based on the outcomes, recommendations are put forward to improve the current energy situation so that the country could catch the pathway towards achieving energy sustainability.

Peer-review under responsibility of the scientific committee of the International Conference on Energy Storage Technology and Power Systems, ESPS, 2022.

Keywords: Energy alternatives; Prioritization; Dimensional reduction; Sustainability

1. Introduction

Sustainability is the driving force behind every country's desire to address emerging environmental and economic concerns as priority. To set targets and engage the countries in a progressive competitive environment, United Nations announced seventeen sustainable development goals (SDGs) associated with 169 targets [1]. Among the SDGs, 'energy access to all (SDG-7)' is found to get mapped with 125 targets out of 169 [2]. The SDG-7 energy trilemma is based on three pillars, energy security, energy equity, and environmental sustainability, all of which contribute to the energy sustainability achievement [3]. And electric power is a critical element of this trilemma, considered as the backbone of any societal infrastructure, enabling breakthroughs in education, livelihoods, and health sectors, and can ensure economic growth and poverty reduction [2].

* Corresponding author.
E-mail addresses: aamir.mehmood@connect.polyu.hk (A. Mehmood), jzhren@polyu.edu.hk (J. Ren).

https://doi.org/10.1016/j.egyr.2022.09.199

Peer-review under responsibility of the scientific committee of the International Conference on Energy Storage Technology and Power Systems, ESPS, 2022.

For developing the strategies for energy sustainability achievement, the energy resources mix that governs the electric energy system of a country and their prioritization to address the electricity demand play a key role. In this concern, multiple researchers attempted to highlight the prioritization of energy alternatives. For instance, Bhandari et al. assessed the electricity generation resources for Nigeria using the analytical hierarchy process (AHP) technique based on qualitative and quantitative assessment information [4]; Saraswat and Digalwar ranked the energy alternatives using the weighted sum model, weighted product model, and WASPAS techniques based on subjective assessment of the decision indicators [5]; Basset et al. analyzed the renewable energy (RE) resources for Egypt using AHP, VIKOR, and TOPSIS techniques based on subjective assessment of the criteria elements [6]; Mostafaeipour et al. ranked the RE resources for Iran using Fuzzy-AHP and extended TODIM techniques based on political, economic, sociocultural, technological, environmental, and legal perspectives of the energy framework [7]. Similarly, many published articles focus on prioritizing energy alternatives for specific countries [8]. However, all the studies involved the full one-dimensionality feature of the assessment information of the decision indicators throughout. To the best of the authors' knowledge, a few studies apply the dimensional reduction feature to the decision indicators to prioritize alternatives.

For the prioritization of energy alternatives, multiple multi-criteria decision-making (MCDM) approaches can be applied [9]. However, there is an MCDM approach called principal component analysis (PCA) based on the dimensional reduction characteristic feature [10]. PCA has been used for analyzing and ranking the alternatives across various disciplines. For instance, Omrani et al. used the PCA approach to calculate the development degrees for the provinces of Iran [11]; Asbahi et al. estimated the energy performance through the energy trilemma index approach using the PCA method [12]; Radovanovic et al. determined the geo-economic index of energy security for Europe using the PCA method. Thus, there is a dearth of the dimensional reduction approach on the dataset of decision indicators for prioritizing energy alternatives to highlight the roadmap to energy sustainability.

To address the identified gap, a decision model constituting operational, economic, technological, environmental, and social dimensions is developed to evaluate the performance of Pakistan's energy alternatives. Sustainability performance scores (SPSs) for energy alternatives are calculated using the dimensional reduction feature on the decision indicators. The concluded performance order of energy alternatives is used to identify future directions for achieving energy sustainability in accordance with SDG-7.

The rest of this paper is organized as follows: Section 2 describes the MCDM method with its distinctive feature of dimensional reduction; the decision indicators are introduced in Section 3; the results of applying the dimensional reduction feature to the evaluation of the energy generation alternatives are elaborated in Section 4; and finally, in Section 5, conclusions are drawn, and some recommendations are put forward that can lead to energy sustainability achievement.

2. Principal Component Analysis (PCA) method

Principal component analysis (PCA) is a multivariate analysis tool first formulated by Pearson [13]. This statistical methodology reduces the dimensions of the dataset by preserving most of the original data's important information [10]. Thus, such a dimensional reduction procedure helps analyze and visualize the scenario with the help of fewer influential indicators than the original large number of variables [14]. The procedural steps of the PCA for analyzing a decision problem are described here [10,12,15].

Step I. To start with, the decision problem is analyzed, and an origin matrix *'X'* holding the *'N'* decision indicators for the *'M'* alternatives is generated, as shown in Eq. (1) [10,15].

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1n} & \cdots & x_{1N} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} & \cdots & x_{mN} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{M1} & \cdots & x_{Mn} & \cdots & x_{MN} \end{bmatrix}_{M\times N} \qquad (N = 1, 2, \ldots, n, \ldots, N;\ M = 1, 2, \ldots, m, \ldots, M) \tag{1}$$

Step II. All indicators should have a positive dimension, which can be ensured by applying Eqs. (2) and (3) to the beneficial- and cost-type decision indicators, respectively [10,12].

$$y_{mn} = \frac{x_{mn} - \min x_m}{\max x_m - \min x_m} \tag{2}$$

$$y_{mn} = \frac{\max x_m - x_{mn}}{\max x_m - \min x_m} \tag{3}$$

where, y_{mn} is an entry in the normalized decision matrix '*Y*' of the nth indicator for the mth alternative, where all decision indicators have a positive dimension.

Step III. The matrix '*Y*' is standardized using Eq. (4), which yields the matrix '$Y^{/}$' [10,12,15].

$$y^{/}_{mn} = \frac{y_{mn} - \overline{y_n}}{s_n} \tag{4}$$

where, $y^{/}_{mn}$ is the standardized value of the nth indicator for the mth alternative; and $\overline{y_n}$ & s_n are average and standard deviation values for the nth indicator. This standardization is performed to maintain the generalization of the variables' sample data. Resultantly, each indicator will have a mean value of zero and a variance value of 1.

Step IV. The correlation matrix '*R*' of the '*N*N*' order for the '*N*' indicators is constructed using the Pearson correlation approach in XLSTAT. This correlation matrix (R) can be used to compute a set of '*N*' eigenvectors, represented by $v(= v_1, v_2, \ldots, v_n, \ldots, v_N)$, and '*N*' eigenvalues represented by $\lambda(= \lambda_1, \lambda_2, \ldots, \lambda_n, \ldots, \lambda_N)$. The eigenvalue(s) and the eigenvector(s) can be computed by using Eqs. (5) and (6), respectively [10,12,15].

$$|R - \lambda_n I_n| = 0 \; (n = 1, 2, \ldots, N) \tag{5}$$

$$R v_n = \lambda_n v_n \tag{6}$$

where, I_n is an identity matrix of size '*1,2, …, N*', λ_n is the eigenvalue for the nth indicator calculated from correlation matrix '*R*', and v_n is the eigenvector for the nth indicator calculated from correlation matrix '*R*'.

Step V. The number of principal components (PCs) to be considered is determined from the constructed eigenvectors based on their corresponding eigenvalues such that $\lambda_n \geq 1.0$. After determining the number of PCs to be considered, a decision matrix (P) is built using the considered PCs, as shown in Eq. (7) [15].

$$P_{nu} = \begin{bmatrix} p_{11} & \cdots & p_{1u} & \cdots & p_{1U} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ p_{n1} & \cdots & p_{nu} & \cdots & p_{nU} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ p_{N1} & \cdots & p_{Nu} & \cdots & p_{NU} \end{bmatrix}_{N\times U} \quad (u = 1, 2, \ldots, U; \text{ and } u \leq n) \tag{7}$$

It is worth noting that when PCA is performed in XLSTAT, a component matrix '*Q*' $(= (\overrightarrow{f_1}, \overrightarrow{f_2}, \ldots, \overrightarrow{f_u}, \ldots, \overrightarrow{f_U})_{nxu})$ showing the loading factors is obtained in results rather than the decision matrix '*P*'.

Step VI. The primary component model for the 'M $(= 1, 2, \ldots, m, \ldots, M)$' alternatives is constructed by using the considered 'U $(= 1, 2, \ldots, u, \ldots, U)$' PCs, as shown in Eq. (8) [12,15].

$$\begin{cases} S_{m1} = p_{11}y^{/}_{m1} + p_{21}y^{/}_{m2} + \cdots + p_{n1}y^{/}_{mn} \\ S_{m2} = p_{12}y^{/}_{m1} + p_{22}y^{/}_{m2} + \cdots + p_{n2}y^{/}_{mn} \\ \vdots \\ S_{mu} = p_{nu}y^{/}_{m1} + p_{n2}y^{/}_{m2} + \cdots + p_{nu}y^{/}_{mn} \end{cases} \quad (m = 1, 2, \ldots, M; u = 1, 2, \ldots, U) \tag{8}$$

where, $S_{mu}(= [s_{m1}, s_{m2}, \ldots, s_{mU}])$ are the PC scores for the mth alternative.

Step VII. To evaluate the performance of the alternatives, the sustainability performance scores (SPSs) for the '*M*' energy alternatives are calculated by using the following relation [12,15]:

$$SPS_{mu} = \lambda^{/}_{u} * S_{mu} \tag{9}$$

where, $\lambda^{/}_{u}(= \lambda_u \Big/ \sum_{u=1}^{U} \lambda_u)$; S_{mu} is the PC score for the mth alternative against the uth PC (/factor loading), and SPS_{mu} represents the SPSs for the mth alternative.

Step VIII. To demonstrate the comparative performance of energy alternatives, all SPSs can be standardized on a scale of 0 to 100 (0 being the worst and 100 being the best performance) using the following relation [15].

$$fSPS_m = \left(\sum_{m=1}^{U} \frac{SPS_{mu} - \min(SPS_{mu})}{\max(SPS_{mu}) - \min(SPS_{mu})} \right) \times 100 \tag{10}$$

where, $\max(SPS_{mu})$ and $\min(SPS_{mu})$ indicate the maximum and minimum SPS_{mu} values for the mth alternative, and $fSPS_m$ represents the percentage final cumulative SPS for the mth alternative based on which the energy generation alternatives can be prioritized.

3. Decision indicators and dataset

To calculate the SPSs of the energy alternatives using the PCA technique, a decision model of eighteen decision indicators is developed for the authors' ongoing work titled *'Multi-facet assessment and ranking of alternatives for conceptualizing sustainable hybrid energy infrastructure in Pakistan based on evidential reasoning driven probabilistic tool'* that is described in Table 1. These indicators are classified under five sustainability dimensions. The assessment information of the decision indicators is collected by considering a case study evaluating the energy alternatives for achieving energy sustainability in Pakistan, as mentioned in Table 2.

Table 1. Decision indicators and sustainability dimensions of the energy model.

Sustainability aspect	Decision indicators	
Operational	System efficiency	OPE-1
	Average availability of ER	OPE-2
	Predicted ER reserves	OPE-2
Economic	Capital cost	EC-1
	O&M cost	EC-2
	Levelized cost of electricity	EC-3
	Fuel cost	EC-4
Technological	Capacity factor	TEC-1
	Expected life of power plant (lifespan)	TEC-2
	Water consumption ($*10^3$)	TEC-3
	Construction time	TEC-4
Environmental	CO_2 emissions	ENV-1
	Noise pollution	ENV-2
	Radioactive life cycle emissions	ENV-3
	Land usage	ENV-4
Social	Job creation	SOC-1
	Mortality rate	SOC-2
	Social acceptance	SOC-3

4. Results and discussions

The dimensional reduction feature of the PCA technique is applied to the collected assessment information of the decision indicators to calculate the SPSs. First, Kaiser–Meyer–Olkin (KMO) and Bartlett's test is performed to check the adequacy of the original data sample. The statistical analysis shows that KMO = 0.6, indicating that the original data sample is adequate [15] for applying the PCA approach.

After ensuring the original data adequacy, the application of the procedural steps of the PCA technique starts with the normalization of the input assessment information by using Eqs. (2) and (3). This step guarantees that all indicators have a positive dimension, and the resultant assessment information is mentioned in Table A.1.

The assessment information summarized in Table A.1 is used further in the PCA method, where the assessment information is first standardized. Following that, a correlation matrix is calculated to highlight the correlation between the decision indicators, as mentioned in Table A.2. The correlation matrix analysis confirms the linear relation between the decision indicators with values ranging between −1 and +1. If two indicators are increasing or decreasing in lockstep, they have a positive correlation. For example, OPE-3 and TEC-4 positively correlate with

Table 2. Assessment information of the decision indicators.

Decision indicators	Unit/scale	Energy generation alternatives						
		Gas	Coal	Nuclear	Solar	Hydro	Wind	Biomass
OPE-1 [16–19]	%	48	39	35	20	90	96	33
OPE-2 [20]	%	91	85.4	96	20	50	38	80
OPE-3 [21–24]	GW	302.046	100	No data	2900	60	360	5
EC-1 [25–27]	USD/kW	1384	3676	6116	883	1870	2270	2543
EC-2 [26]	USD/kW-year	27.46	45.08	111.00	15.25	29.86	72.57	130.55
EC-3 [27–29]	USD/MWh	92	114	68	57	44	61.5	76
EC-4 [30,31]	USD/kWh	0.06	0.04	0.47	0	0	0	0
TEC-1 [16,19]	%	11.4	63.8	90.3	25	50	34	50
TEC-2 [19,32,33]	Years	30	30	30	30	100	20	40
TEC-3 [34]	L/MWh	1.875	0.53–2.1	3.1–74.9	0	0.26	0	180.9–969.0
TEC-4 [35–37]	Years	3	5.5	5	1	5	4.5	3
ENV-1 [38]	gCO2 eq./kWh	499	888	24.2	300	74.9	66.35	650
ENV-2 [39]	dBa	30	30	20	10	15	20	30
ENV-3 [40]	Person-rem/year	0	490	4.8	0	0	0	0
ENV-4 [19,41]	km^2/1000 MW	0.8	3.7	2.5	35	750	100	5000
SOC-1 [19,42]	Persons/500 MW	2250	2350	2500	5370	2500	5635	36,055
SOC-2 [43]	Deaths/TWh	2.8	24.6	0.07	0.02	0.02	0.04	4.6
SOC-3	1–5	4.5	2.5	3.5	3.5	4	3	2.5

a 0.799 correlation value. On the contrary, if one indicator's value increases and the other's decreases, we can say that the two are negatively correlated e.g., TEC-3 and SOC-1. If there is no relationship between two indicators, they will have zero correlation.

Following that, the correlation matrix *'R'* is used to determine the eigenvectors and eigenvalues. This is accomplished by applying the single value decomposition (SVD) approach to the correlation matrix. The eigenvectors represent the coefficients of principal components (PCs). Based on the eigenvalues, the number of eigenvectors/PCs are selected, i.e., only those PCs are considered which possess maximum variance value(s) (i.e., eigenvalue(s)). The PCs are the linear combination weights of 18 decision indicators. The first PC exhibits the maximum variance, while the second one has the most variance out of the rest of the indicators. The eigenvalues, variability, and cumulative scores for each of the considered PCs are mentioned in Table 3, and the considered PCs are tabulated in Table 4, such that $\lambda_n \geq 1.0$.

Table 3. Eigenvalues, variability, and cumulative scores of factor loadings.

	F1	F2	F3	F4	F5
Eigenvalue	6.627	3.884	3.571	1.673	1.551
Variability (%)	36.819	21.578	19.840	9.293	8.615
Cumulative (%)	36.819	58.396	78.237	87.530	96.145

The statistical information in Table 3 is used to determine which factor loadings to use for PCA since they represent the correlation and variability between the indicators. Each factor loading should have a variability value between 0%–100%. The factor loading 'F1' has a maximum variability of 36.819%; 'F2', 'F3', and 'F4' have variability of 21.578%, 19.840%, and 9.293%, respectively. Form this, two-factor loadings F1 and F2 with the highest degree of variability are selected for further PCA method-based evaluation.

To compute the PC scores, the standardized input matrix is multiplied by the considered PCs mentioned in Table 4. The resultant PC scores are mentioned in Table 5. To proceed with the SPSs computations, the weighted eigenvalues ($\lambda_u^{/}$) are calculated, as illustrated in Table 6. Then, each PC score for all factor loadings is multiplied by the corresponding weighted eigenvalue ($\lambda_u^{/}$), and the results are tabulated in Table 7. Lastly, the final cumulative SPSs for all energy alternatives are calculated using Eq. (10). The cumulative final score values are mentioned in Table 8. Based on these final SPSs ($fSPS_m$), the energy generation alternatives are prioritized as portrayed in

Table 4. The considered principal components (PCs).

Indicators	F1	F2	F3	F4	F5
OPE-1	−0.338	0.036	−0.086	0.268	−0.122
OPE-2	0.323	−0.111	0.052	−0.148	0.361
OPE-2	−0.261	0.091	−0.142	−0.306	−0.357
EC-1	−0.259	0.264	−0.245	0.067	0.197
EC-2	−0.253	−0.149	−0.341	0.056	0.139
EC-3	−0.277	0.051	0.339	0.182	−0.088
EC-4	−0.135	0.297	−0.311	0.314	0.055
TEC-1	0.232	−0.210	0.257	0.162	−0.298
TEC-2	−0.104	−0.015	0.127	0.588	0.273
TEC-3	−0.183	−0.418	−0.160	−0.027	−0.006
TEC-4	−0.194	0.302	−0.072	−0.431	−0.042
ENV-1	−0.229	−0.173	0.371	0.023	−0.035
ENV-2	−0.314	−0.094	0.154	0.064	−0.334
ENV-3	−0.213	0.153	0.359	−0.189	0.221
ENV-4	−0.151	−0.430	−0.155	−0.139	−0.044
SOC-1	0.146	0.451	0.134	0.031	−0.044
SOC-2	−0.249	0.075	0.365	−0.164	0.148
SOC-3	−0.221	−0.173	0.055	−0.167	0.554

Table 5. Principal component (PC) scores.

Alternatives	1	2	3	4	5
Gas	−1.72583	−0.41251	−0.12255	−0.45172	1.428498
Coal	−0.43727	−0.78591	−0.76118	0.304608	0.298844
Nuclear	−0.97947	−1.17714	1.374088	−0.37365	0.449664
Solar	−2.97284	−0.03237	0.002521	−0.32145	0.025321
Hydro	−2.43233	−0.57594	0.653682	0.847928	0.850801
Wind	−2.13812	−0.33915	0.426982	0.17362	0.282062
Biomass	−0.61887	1.101499	0.74189	0.089645	0.591338

Table 6. Weighted eigenvalue values ($\lambda_u^/$) of the considered principal components.

	1	2	3	4	5
$\lambda_u^/$	0.382954	0.224428	0.206359	0.096659	0.0896

Table 7. SPS_{mu} values of the energy generation alternatives.

Alternatives	F1	F2	F3	F4	F5	max	min
Gas	−0.66091	−0.09258	−0.02529	−0.04366	0.127993	0.127993	−0.66091
Coal	−0.16745	−0.17638	−0.15708	0.029443	0.026776	0.029443	−0.17638
Nuclear	−0.37509	−0.26418	0.283555	−0.03612	0.04029	0.283555	−0.37509
Solar	−1.13846	−0.00727	0.00052	−0.03107	0.002269	0.002269	−1.13846
Hydro	−0.93147	−0.12926	0.134893	0.08196	0.076231	0.134893	−0.93147
Wind	−0.8188	−0.07611	0.088111	0.016782	0.025273	0.088111	−0.8188
Biomass	−0.237	0.247208	0.153096	0.008665	0.052984	0.247208	−0.237

Fig. 1. The analysis of Fig. 1 elaborates that solar is the most favorable energy alternative, followed by wind > hydro > gas > biomass > nuclear > coal.

5. Conclusions and recommendations

This work aimed to evaluate the performance of energy alternatives for achieving sustainability using the distinctive dimensional reduction feature. For this purpose, an energy model comprising eighteen decision indicators grouped into five sustainability dimensions is considered for prioritizing the energy generation alternatives of

Table 8. Final sustainability performance scores (*fSPSs*) of the energy generation alternatives.

Alternatives	F1	F2	F3	F4	F5	Final scores	%-final scores	Rank order
Gas	0	0.720407	0.805704	0.782413	1	0.661705	66.17047	4
Coal	0.043373	0	0.093791	1	0.987043	0.424841	42.48415	7
Nuclear	0	0.168391	1	0.514656	0.63066	0.462741	46.27412	6
Solar	0	0.991642	0.998467	0.970773	1	0.792176	79.21763	1
Hydro	0	0.75229	1	0.950361	0.944989	0.729528	72.95281	3
Wind	0	0.818919	1	0.921349	0.930711	0.734196	73.41958	2
Biomass	0	1	0.805636	0.507352	0.598881	0.582374	58.23739	5

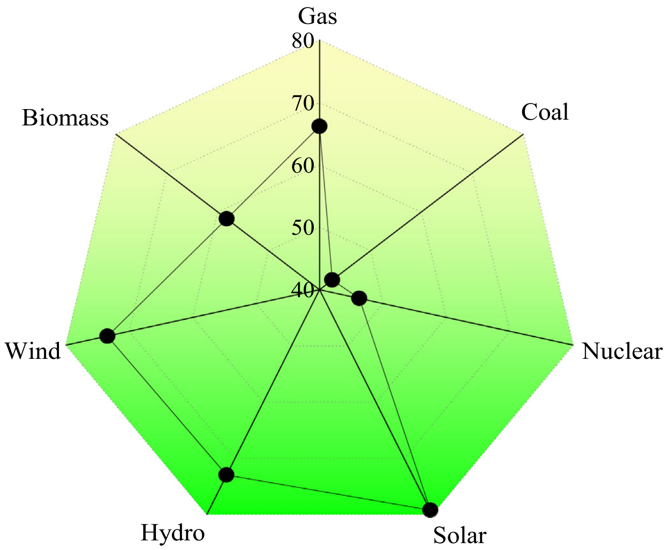

Fig. 1. The final SPS scores-based prioritization of the energy generation alternatives.

Pakistan's energy mix based on their calculated sustainability performance scores. The primary outcomes are as follows:

- Compared to the traditional MCDM methods that use complete one-dimensionality of the decision indicators, the dimensional reduction feature can prioritize the energy generation alternatives vigorously.
- The application of the dimensional reduction approach prioritizes the energy alternatives for Pakistan in the following order: solar > wind > hydro > gas > biomass > nuclear > coal.

Moreover, in the light of the study's findings, we put forward the following policy recommendations that can lead to energy sustainability achievement:

- Energy usage in the era of SDGs and the Paris Agreement should be affordable and clean. For this, clean energy resources such as hydro, solar, and wind should be prioritized over coal installations, as evidenced by the outcomes, rather than the coal projects currently underway in Pakistan.
- Energy planning should consider short- and long-term goals to meet current demands and foresee.
- Rather than constantly overburdening the government, certain attractive incentive measures should be introduced to stimulate practical renewables installations at the domestic level.

The current work utilizes the dimensional reduction feature to prioritize energy alternatives through a decision model to ensure a sustainable future. However, this trait makes it difficult to investigate the comparative impact of the particular decision dimensions on alternatives' final scores. Further, the proposed decision model can be revised, and the concluded prioritization order can be compared to other MCDM methods dealing with complete dimensional information. In addition, the case study work can be extended to other countries, especially those still struggling to devise strategies for making the country's energy mix of renewables dominant. A comparison can be performed to accelerate the action plans for energy sustainability achievement.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

Acknowledgments

The work presented was supported by the grant from the Research Grant Council. The Hong Kong Ph.D. Fellowship (Ph.D. Fellowship awardee: Aamir Mehmood), Research Committee of The Hong Kong Polytechnic University, Hong Kong under student account code RLMD, and the Departmental General Research Funds of the Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University (G-UAFT).

Appendix

See Tables A.1 and A.2.

Table A.1. Normalized assessment information (ensured positive dimension of all the indicators).

Observations	Gas	Solar	Coal	Nuclear	Biomass	Wind	Hydro
OPE-1	0.368421	0.25	0	0.921053	0.921053	1	0.171053
OPE-2	0.934211	0.860526	1	0	0.394737	0.236842	0.789474
OPE-3	0.104154	0.034483	0	1	0.02069	0.124138	0.001724
EC-1	0.904261	0.466272	0	1	0.811389	0.734951	0.682782
EC-2	0.894102	0.741284	0.169558	1	0.873287	0.502862	0
EC-3	0.314286	0	0.657143	0.814286	1	0.75	0.542857
EC-4	0.87234	0.914894	0	1	1	1	1
TEC-1	0	0.664132	1	0.17237	0.489227	0.286439	0.489227
TEC-2	0.125	0.125	0.125	0.125	1	0	0.25
TEC-3	0.996739	0.997713	0.932168	1	0.999548	1	0
TEC-4	0.555556	0	0.111111	1	0.111111	0.222222	0.555556
ENV-1	0.450336	0	1	0.680713	0.941306	0.951204	0.275527
ENV-2	0	0	0.5	1	0.75	0.5	0
ENV-3	1	0	0.990204	1	1	1	1
ENV-4	1	0.99942	0.99966	0.993159	0.850136	0.980157	0
SOC-1	0	0.002958	0.007395	0.092294	0.007395	0.100133	1
SOC-2	0.8869	0	0.997966	1	1	0.999186	0.81367
SOC-3	1	0	0.5	0.5	0.75	0.25	0

Table A.2. The correlation matrix (R).

Indicators	OPE-1	OPE-2	OPE-3	EC-1	EC-2	EC-3	EC-4	TEC-1	TEC-2	TEC-3	TEC-4	ENV-1	ENV-2	ENV-3	ENV-4	SOC-1	SOC-2	SOC-3
OPE-1	1	−0.918	0.490	0.695	0.594	0.613	0.610	−0.560	0.294	0.411	0.247	0.444	0.678	0.291	0.297	−0.288	0.384	0.228
OPE-2	−0.918	1	−0.717	−0.625	−0.456	−0.644	−0.537	0.454	−0.142	−0.247	−0.450	−0.393	−0.785	−0.297	−0.167	0.113	−0.387	−0.020
OPE-3	0.490	−0.717	1	0.512	0.512	0.291	0.257	−0.454	−0.214	0.239	0.799	0.091	0.649	0.183	0.250	−0.144	0.241	0.123
EC-1	0.695	−0.625	0.512	1	0.623	0.224	0.865	−0.921	0.188	0.024	0.636	−0.111	0.207	0.259	−0.070	0.082	0.216	0.299
EC-2	0.594	−0.456	0.512	0.623	1	0.027	0.442	−0.582	0.228	0.720	0.240	−0.016	0.372	−0.160	0.646	−0.670	−0.077	0.539
EC-3	0.613	−0.644	0.291	0.224	0.027	1	0.013	−0.060	0.498	0.049	0.213	0.841	0.818	0.767	−0.037	0.000	0.841	0.318
EC-4	0.610	−0.537	0.257	0.865	0.442	0.013	1	−0.710	0.203	−0.142	0.332	−0.367	−0.026	−0.096	−0.249	0.249	−0.153	−0.131
TEC-1	−0.560	0.454	−0.454	−0.921	−0.582	−0.060	−0.710	1	0.098	−0.112	−0.650	0.105	−0.045	−0.302	−0.066	0.015	−0.248	−0.410
TEC-2	0.294	−0.142	−0.214	0.188	0.228	0.498	0.203	0.098	1	0.012	−0.250	0.258	0.304	0.165	−0.141	−0.043	0.188	0.329
TEC-3	0.411	−0.247	0.239	0.024	0.720	0.049	−0.142	−0.112	0.012	1	−0.217	0.363	0.427	−0.179	0.985	−0.988	−0.013	0.503
TEC-4	0.247	−0.450	0.799	0.636	0.240	0.213	0.332	−0.650	−0.250	−0.217	1	−0.071	0.285	0.457	−0.194	0.293	0.395	0.194
ENV-1	0.444	−0.393	0.091	−0.111	−0.016	0.841	−0.367	0.105	0.258	0.363	−0.071	1	0.719	0.699	0.329	−0.347	0.819	0.453
ENV-2	0.678	−0.785	0.649	0.207	0.372	0.818	−0.026	−0.045	0.304	0.427	0.285	0.719	1	0.428	0.370	−0.363	0.574	0.285
ENV-3	0.291	−0.297	0.183	0.259	−0.160	0.767	−0.096	−0.302	0.165	−0.179	0.457	0.699	0.428	1	−0.202	0.206	0.979	0.505
ENV-4	0.297	−0.167	0.250	−0.070	0.646	−0.037	−0.249	−0.066	−0.141	0.985	−0.194	0.329	0.370	−0.202	1	−0.979	−0.039	0.461
SOC-1	−0.288	0.113	−0.144	0.082	−0.670	0.000	0.249	0.015	−0.043	−0.988	0.293	−0.347	−0.363	0.206	−0.979	1	0.044	−0.532
SOC-2	0.384	−0.387	0.241	0.216	−0.077	0.841	−0.153	−0.248	0.188	−0.013	0.395	0.819	0.574	0.979	−0.039	0.044	1	0.540
SOC-3	0.228	−0.020	0.123	0.299	0.539	0.318	−0.131	−0.410	0.329	0.503	0.194	0.453	0.285	0.505	0.461	−0.532	0.540	1

References

[1] 17 goals to transform our world. Sustainable Development Goals - United Nations; 2021, Retrieved at: <https://www.un.org/sustainabledevelopment/>. (accessed on 20 Nov 2021).

[2] Bukari Dramani, Kemausuor Francis, Quansah David A, Adaramola Muyiwa S. Towards accelerating the deployment of decentralised renewable energy mini-grids in Ghana: Review and analysis of barriers. Renew Sustain Energy Rev 2021;135:110408.

[3] World energy trilemma index. World Energy Council; 2021, retrieved at: <https://www.worldenergy.org/transition-toolkit/world-energy-trilemma-index>. (accessed on 20 Nov 2021).

[4] Bhandari Ramchandra, Arce Benjamin Eduardo, Sessa Vittorio, Adamou Rabani. Sustainability assessment of electricity generation in niger using a weighted multi-criteria decision approach. Sustainability 2021;13(1):385.

[5] Saraswat SK, Digalwar Abhijeet K. Empirical investigation and validation of sustainability indicators for the assessment of energy sources in India. Renew Sustain Energy Rev 2021;145:111156.

[6] Abdel-Basset Mohamed, Gamal Abdullah, Chakrabortty Ripon K, Ryan Michael J. Evaluation approach for sustainable renewable energy systems under uncertain environment: A case study. Renew Energy 2021;168:1073–95.

[7] Mostafaeipour Ali, Sedeh Ali Sadeghi, Chowdhury Shahariar, Techato Kuaanan. Ranking potential renewable energy systems to power on-farm fertilizer production. Sustainability 2020;12(19):7850.

[8] Rigo Paula Donaduzzi, Rediske Graciele, Rosa Carmen Brum, Gastaldo Natalia Gava, Michels Leandro, Junior Alvaro Luiz Neuenfeldt, Siluk Julio Cezar Mairesse. Renewable energy problems: Exploring the methods to support the decision-making process. Sustainability 2020;12(23):10195.

[9] Lin Ruojue, Ren Jingzheng. Overview of multi-criteria decision analysis and its applications on energy systems. In: Energy systems evaluation (Volume 2). Springer; 2021, p. 1–26.

[10] Geladi Paul, Linderholm Johan. Principal component analysis. In: Reference module in chemistry, molecular sciences and chemical engineering. Elsevier; 2020.

[11] Omrani Hashem, Valipour Mahsa, Mamakani Saeid Jafari. Construct a composite indicator based on integrating Common Weight Data Envelopment Analysis and principal component analysis models: An application for finding development degree of provinces in Iran. Socio-Econ Plan Sci 2019;68:100618.

[12] Al Asbahi Ahmed Abdulwali Mohammed Haider, Gang Feng Zhi, Iqbal Wasim, Abass Qaiser, Mohsin Muhammad, Iram Robina. Novel approach of principal component analysis method to assess the national energy performance via Energy Trilemma Index. Energy Rep 2019;5:704–13.

[13] Pearson karl. LIII. On lines and planes of closest fit to systems of points in space. Lond Edinb Dublin Philos Mag J Sci 1901;2(11):559–72.

[14] Ringnér Markus. What is principal component analysis? Nature Biotechnol 2008;26(3):303–4.

[15] Xiao Huijuan, Zhang Long, Ren Jingzheng. Sustainability risks of resource-exhausted cities in China: A principal component analysis. In: Multi-criteria decision analysis for risk assessment and management. Springer; 2021, p. 225–49.

[16] Power purchase price forecast, FY 2019-20. Central Power Purchasing Agency (CPPA), retrieved at: <https://nepra.org.pk/Admission%20Notices/2019/09-September/CPPA-G%20Report%20on%20PPP.pdf>. (accessed on 1 Nov 2021).

[17] Photovoltaic energy factsheet. Cener for Sustainable Systems, University of Michigan, retrieved at: <https://css.umich.edu/factsheets/photovoltaic-energy-factsheet> (accessed on 1 Nov 2021).

[18] Hydroelectric power. U.S. Department of the Interior Bureau of Reclamation, retrieved at: <https://www.usbr.gov/power/edu/pamphlet.pdf> (accessed on 1 Nov 2021).

[19] Solangi Yasir Ahmed, Tan Qingmei, Mirjat Nayyar Hussain, Valasai Gordhan Das, Khan Muhammad Waris Ali, Ikran Muhammad. An integrated Delphi-AHP and fuzzy TOPSIS approach toward ranking and selection of renewable energy resources in Pakistan. Processes 2019;7(2):118.

[20] Chatzimouratidis Athanasios I, Pilavachi Petros A. Technological, economic and sustainability evaluation of power plants using the Analytic Hierarchy Process. Energy Policy 2009;37(3):778–87.

[21] Shah Syed Ahsan Ali, Solangi Yasir Ahmed. A sustainable solution for electricity crisis in Pakistan: opportunities, barriers, and policy implications for 100% renewable energy. Environ Sci Pollut Res 2019;26(29):29687–703.

[22] Solangi Yasir Ahmed, Longsheng Cheng, Shah Syed Ahsan Ali. Assessing and overcoming the renewable energy barriers for sustainable development in Pakistan: An integrated AHP and fuzzy TOPSIS approach. Renew Energy 2021;173:209–22.

[23] Pakistan's coal power generation potential. Private Power and Infrastructure Board, retried at: <https://embassyofpakistanusa.org/ wp-content/uploads/2017/05/Thar-Coal-Power-Generation.pdf> (accessed on 1 Nov 2021).

[24] Country energy overview – Pakistan. Pakistan Atomic Energy Commission - IAEA, retreived at:<https://www-pub.iaea.org/MTCD/publications/PDF/cnpp2019/countryprofiles/Pakistan/Pakistan.htm> (accessed on 1 Nov 2021).

[25] Capital costs of utility-scale solar PV in selected emerging economies. International Energy Agency, retrieved at: <https://www.iea.org/data-and-statistics/charts/capital-costs-of-utility-scale-solar-pv-in-selected-emerging-economies> (accessed on 1 Nov 2021).

[26] Capital cost and performance characteristic estimates for utility scale electric power generating technologies. U.S. Energy Information Administration, retrieved at: <https://www.eia.gov/analysis/studies/powerplants/capitalcost/> (accessed on 1 Nov 2021).

[27] Renewable power generation costs. International Renewable Energy Agency, retrieved at: <https://www.irena.org/publications/2021/Jun/Renewable-Power-Costs-in-2020> (accessed on 1 Nov 2021).

[28] Projected costs of generating electricity (2020 edition). Intrnatinal Energy Agency - Nuclear Energy Agency.

[29] Moore Jon, Bullard Nat. Power, transport, buildings and industry, commodities, food and agriculture, capital. In: BNEF executive factbook. 2021.

[30] State of industry report – 2020. Pakistan: National Electric Power Regulatory Authority.

[31] Uranium marketing annual report. U.S. Energy Information Administration; 2021, retrieved at: <https://www.eia.gov/uranium/marketing/>.
[32] Shahid Muhammad Saleem, Lodhi Rab Nawaz, Gill Abid Rashid. An energy transition model for Pakistan's electricity system: Scenarios and their implications. Environ Prog Sustain Energy 2019;38(5):13210.
[33] Energy analysis. National Renewable Energy Laboratory, retrieved at: <https://www.nrel.gov/analysis/tech-footprint.html> (accessed on 1 Nov 2021).
[34] Jones Willie. How much water does it take to make electricity? IEEE Spectr 2008. retrieved at: <https://spectrum.ieee.org/how-much-water-does-it-take-to-make-electricity>.
[35] Median construction time required for nuclear reactors worldwide. Statista, retrieved at: <https://www.statista.com/statistics/712841/median-construction-time-for-reactors-since-1981/> (accessed on 1 Nov 2021).
[36] Wynn Gerrd. Solar is fastest power plant to install. Britain; retrieved at: <https://energyandcarbon.com/solar-pv-fastest-power-plant-install/> (accessed on 1 Nov 2021).
[37] Lee Hyun-Chul, Lee Eul-Bum, Alleman Douglas. Schedule modeling to estimate typical construction durations and areas of risk for 1000 MW Ultra-Critical Coal-Fired power plants. Energies 2018;11(10):2850.
[38] Amponsah Nana Yaw, Troldborg Mads, Kington Bethany, Aalders Inge, Hough Rupert Lloyd. Greenhouse gas emissions from renewable energy sources: A review of lifecycle considerations. Renew Sustain Energy Rev 2014;39:461–75.
[39] Topcu YI, Ulengin F. Energy for the future: An integrated decision aid for the case of Turkey. Energy 2004;29(1):137–54.
[40] Chatzimouratidis Athanasios I, Pilavachi Petros A. Multicriteria evaluation of power plants impact on the living standard using the analytic hierarchy process. Energy Policy 2008;36(3):1074–89.
[41] The ultimate fast facts guide to nuclear energy. U.S. Department of Energy, retrieved at: <https://www.energy.gov/sites/default/files/2019/01/f58/Ultimate%20Fast%20Facts%20Guide-PRINT.pdf>. (accessed on 1 Nov 2021).
[42] Widiyanto Anugerah, Kato Seizo, Maruyama Naoki. Optimizing selection of appropriate power generation systems in Indonesia by using distance based approach method. J Energy Resour Technol 2004;126(1):63–71.
[43] Ritchie Hannah. What are the safest and cleanest sources of energy? Our World in Data; 2020, retrieved at: <https://ourworldindata.org/safest-sources-of-energy>.