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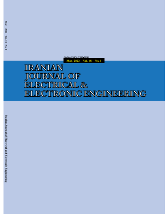

Sensitivity Analysis Based Comparative Assessment of Resource Mix Using MCDM Technique: A Case Study of Thar Desert, India

N. Thakkar* and P. Paliwal*(C.A.)

Abstract: In the last decade, there has been a lot of focus on sustainable development in the electrical power industry to meet the growing energy demand. This has led to an increase in the integration of renewable energy sources (RES). In addition to being abundantly available, the RES offers advantages such as low environmental impact and increased social development of rural communities which are imperative for a sustainable society. However, the selection of a particular generating resource or resource mix (RM) for an autonomous micro-grid is a complex problem that involves multiple conflicting factors. In this paper, a planning strategy for selecting an appropriate RM has been proposed. Seven RMs comprising different combinations of four generation/storage technologies such as solar photovoltaic array (SPVA), wind turbine (WT), diesel generator (DG) and battery storage (BS) have been considered. The planning is initiated with the determination of optimal component sizing for all seven RMs. The RMs are then analyzed with respect to four primary sustainability parameters i.e. economic, social, technical and environmental. The analysis is further enhanced by investigation of 13 sub-parameters as well. Thereafter, prioritization of RMs is carried out using two MCDM methods: Best worst method (BWM) and PROMETHEE II. Finally, to assert the importance of weight assignment on RM ranking, sensitivity analysis is performed. In order to impart the practical aspect to analysis, the planning formulation is applied to a case study of the Thar desert, India. The results suggest that a combination of SPVA and BS provides the most optimum RM solution.

Keywords: BWM, MCDM, PROMETHEE II, Sensitivity Analysis, Sustainable Planning.

Nomenclature

ACC	Annualized cycle cost [$]
BWM	Best worst method
BS	Battery storage
CC	Capital cost [$]
CE	Carbon equivalent emission
DG	Diesel generator
EENS	Expected energy not served [kWh]
JC	Job creation
LU	Land utilization [km^2]
LOLE	Loss of load expectation [Hours]
LCOE	Levelized cost of energy [$/kWh]
LCC	Life cycle cost [$]
MCDM	Multi criteria decision making
PSO	Particle swarm optimization
PROMETHEE	Preference ranking organization method for enrichment evaluation
RES	Renewable energy sources
RM	Resource mix
SPVA	Solar photovoltaic array
SOC	State of charge
WT	Wind turbines

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1 Introduction

IN the present times, there are rising concerns about augmenting energy demand and depleting fossil fuel reserves. The climate change protocols further pose a challenge in front of electric power industries across the world. Currently, India stands in the third position in energy consumption and third in energy production [1]. With the consistent efforts of the Ministry of new and renewable energy, India has made tremendous growth in the last decade and now stands in fourth position in installed renewable energy (RE) capacity [2]. India has targeted to achieve around 50 percent of the energy requirement from RE sources by 2030 [3]. Renewable energy sources (RES) are offering a clean and low-cost way of energy production [4]. However, integration of RES is associated with various challenges; the prominent ones being low reliability, uncertainty in power production and high initial cost. The hybridization of RES with energy storage technology or diesel source is seen as an option to alleviate these problems. The battery storage system has emerged as one promising technology which can render reliability to RES integration with minimal effect on environmental conditions. The selection of optimum resource mix (RM) is mostly region specific and involves analysis of numerous parameters [5]. It is imperative to analyze different economic, environmental, social and technical aspects in RM, planning and selection for sustainable planning. In this regard, MCDM methods have emerged as an effective way of performing multiple parameter based planning analyses to finalize an RM. The MCDM methods are a group of approaches that involve selection, prioritization and ranking of alternatives based on multiple parameters [6].

1.1 Literature Survey

In the literature, several studies have been reported on the analysis of RM in microgrid planning. In Ref. [7], Kumar *et al*. investigated the sustainability parameters of different RMs of locally available sources by using a proposed bi-level MCDM based framework in the rural hill area of India. In Ref. [8], Athila *et al*. presents an optimization based framework for the sustainability parameter analysis of different energy resources in Rottenest Island, Australia. In Ref. [9] Taisif *et al*. analyzed the sustainable parameter based evaluation for renewable based RM in the southern location of Bangladesh. Kumar *et al*. [10] analyzed the economic and environmental parameters of five different energy resources for the selection of the most appropriate resource for energy generation in the location of BHU campus, India. In Ref. [11], Wang analyzed the sustainable characteristics of four different energy resources to determine the best energy source alternative for energy generation in Vietnam. In Ref. [12], author analyzed the sustainability parameters of eight different energy resources in four south Asian countries. In Ref. [13], Perez *et al.* used ANP model for the analysis and assessment of a hybrid micro-grid located in Honduran Mesoamerican Dry Corridor. In Ref. [14], Lee *et al.* investigated the behavior of different MCDM methods in RES ranking for a case study in Taiwan. In Ref. [15], Bhowmik *et al*. compared different MCDM methods for RES selection in Tripura, India. In Ref. [16], Ali *et al.* ranked different energy resources by using MCDM model for the case study of Bangladesh. In Ref. [17] Wang *et al.* employed a MCDM based model to select best resource alternative amongst four different RES for a location in Vietnam. Authors in Ref. [18] utilized the MCDM method for the best technology selection of waste to energy conversion. In Ref. [19] Alao *et al.* developed entropy and TOPSIS based model to rank best waste to energy technology. In Ref. [20] Almutairi *et al.* analyzed and ranked the combination of four energy technologies by using SWARA and WASPAS methods. Author in Ref. [21] and Ref. [22] employed AHP method for the RES ranking based on sustainability criteria. In Ref. [23] Agheb *et al*. employed Integer PSO for optimal sizing and placement of wind turbine in a distribution system. In Ref. [24] Boukaroura *et al*. employed Dragonfly optimization for the optimal sizing and placement of multiple RES. In Ref. [25] Hassanzadehfard *et al*. applied PSO to obtain DG unit sizing and placement by considering the load variation. Table 1 shows the summary of the literature survey on the implementation of MCDM methods for different case studies.

1.2 Research Gaps and Paper Contributions

Based on the literature survey, the research gaps and consequent contributions of this paper are summarized as follows:

i. The analysis of literature survey has reflected that majority of the optimal sizing and determination of resource mix studies do not provide a detailed evaluation of environmental and social criteria. The environmental analysis is largely focused on carbon emissions. In this work, in order to present a larger perspective of environmental analysis, three major environmental criteria *viz*. water consumption, carbon equivalent emission and land utilization have been considered. The social criteria involve inclusion of job creation and worker safety. The novelty of this paper lies in the fact that majority of papers focus on one or two major factors whereas this work renders a comprehensive assessment based on different sustainability parameters. This facilitates enhanced decision making for system planners.

ii. The literature survey also indicated that MCDM methods have been majorly deployed for prioritization of power generation resources [7], [9-22]. However, the studies analyzing RM using MCDM have been scarcely reported [16-18], [20]. Moreover, the determination of MCDM based RM reported in literature is not initiated on the platform of optimal component sizing [17, 18]. The present work

Table 1 Summary of literature survey on the implementation of MCDM methods.

Ref.	Year	Planning technique	Sensitivity analysis	Analysis of RM	Optimization technique	Uncertainty analysis	Application of MCDM	Sustainability criteria evaluation: Economic	Technical	Social	Environmental	Location	Objective
[7]	2019	AHP	×	✓	×	×	✓	✓	✓	✓	✓	Kameng, India	Assessment of sustainable micro-grid
[8]	2018	HOMER	✓	×	✓	×	×	✓	✓	✓	×	Rottnest Island, Australia	Analysis and assessment of different energy systems based on technical social and economic criteria.
[9]	2019	ENTROPY, EDAS	×	×	×	×	✓	✓	✓	✓	✓	Bangladesh	Analysis and assessment of RES.
[10]	2017	AHP, VIKOR	×	×	×	×	✓	✓	✓	✓	×	BHU campus, India	Assessment of RES.
[11]	2021	G-AHP, WASPAS	×	×	×	×	✓	✓	✓	✓	✓	Vietnam	Selection of appropriate RES.
[12]	2020	GLOBAL, MCDA model	×	×	×	×	✓	✓	×	✓	✓	South Asia	Sustainability assessment of four different countries in South Asia.
[13]	2020	ANP	×	×	×	×	✓	✓	✓	✓	✓	Honduran Mesoamerican Dry Corridor	Analysis and assessment of energy generation resource
[14]	2018	ENTROPY, WSM, VIKOR, TOPSIS, ELECTRE	✓	×	×	×	✓	✓	✓	✓	✓	Taiwan	Analysis of different MCDM methods for RES ranking
[15]	2019	ENTROPY, COPRAS, MOOSRA, TOPSIS	✓	×	×	×	✓	✓	✓	×	×	Tripura, India	Analysis of different MCDM methods for RES ranking
[16]	2020	EDAS, BWM, IDOCRIW	✓	×	✓	×	✓	✓	✓	✓	✓	Bangladesh	Analysis and ranking of energy generation resources.
[17]	2022	EDAS, SWARA, Homer pro	×	✓	✓	×	✓	✓	×	×	✓	Isfahan, Iran	Selection of best RM.
[18]	2022	TODIM, MULTIMOOSRAL	×	×	✓	×	✓	×	✓	×	×	Tehran city, Iran	Waste to energy conversion technology selection
[19]	2020	ENTROPY, TOPSIS	×	×	×	×	✓	✓	✓	×	✓	Lagos, Nigeria	Waste to energy conversion technology selection
[20]	2021	SWARA, WASPAS	✓	✓	✓	×	✓	✓	✓	×	✓	Hormozgan, Iran	Selection of best RM.
[21]	2014	AHP	×	×	×	×	✓	✓	✓	✓	✓	Malaysia	Selection of best renewable resource
[22]	2009	AHP	✓	×	×	×	✓	✓	✓	✓	✓	Iran	Selection of best renewable resource
[23]	2021	Integer-PSO	×	×	✓	✓	×	×	✓	×	×	Iran	Sizing and placement RES in distribution system.
[24]	2020	Dragonfly Optimization	×	✓	✓	×	×	✓	✓	×	×	-	Load variation based analysis of resource mix.
[25]	2018	PSO	×	✓	✓	✓	×	×	✓	×	×	-	Load growth based optimal sizing of RES.
Proposed work	-	PSO, BWM, PROMETHEE II	✓	✓	✓	✓	✓	✓	✓	✓	✓	India	Optimal selection of RM based on the sustainability criteria using MCDM and optimization technique.

assimilates optimal component sizing in MCDM structure and embeds it in sustainability evaluation framework. In this work, seven optimally sized RMs consisting of four technologies (SPVA, WT, BS and DG) have been prioritized based on thirteen major sustainability criteria.

iii. Sensitivity analysis in RM prioritization has been seldom reported in the literature. The studies reporting sensitivity analyses are mostly focused on the impact of variation of generation/load [23, 24]. In this study, BWM is used for sensitivity analysis. The primary weights of all four parameters (Economic, technical, social and environmental) are changed from 100 percent to 30 percent and their effect on the final weight of sub-parameters and RM rankings is analyzed.

The remaining paper is organized as follows: Section 2 explains the methodology along with the description of RM, sustainability parameters and MCDM methods. Section 3 highlights the case study. In Section 4, results and discussion has been presented. The results of optimal sizing, RM sustainability evaluation, RM priority and sensitivity analysis have been discussed in detail. Finally, the conclusion of the paper with suggestions for future work has been presented in Section 5.

2 Methodology

A schematic representation of methodology is depicted in Fig. 1. The planning is initiated with the identification of different RMs based on the climatological parameters of the site under consideration. Thereafter, optimal component sizes corresponding to each RM are obtained using particle swarm optimization (PSO) [4]. A discussion on objective function and constraints is presented in the following sub-section. The RM are grouped under three categories. The first category comprises conventional generator (DG), the second category consists of a combination of renewable energy resources and conventional generator (DG), and in the third category combination of renewable resources with battery storage is considered. After determining the optimal sizes, each RM is evaluated on the basis of sustainability parameters. The sustainability parameters are discussed in the following sub-section. Thereafter, MCDM method is applied for RM prioritization. A sensitivity analysis is also performed in order to determine the impact of parameter weights on RM prioritization.

2.1 Resource Characteristics and Mix

The formulation of RM is obtained based on the characteristics of the considered technology. Since the solar photovoltaic array (SPVA) and wind turbine (WT) are intermittent energy sources, these resources are combined with battery storage (BS) or diesel generator (DG) technology to maintain system reliability. Table 2 shows different RMs considered in this paper.

Table 2 RM scenarios of all four resources.

RM	Resources
RM 1	DG only
RM 2	WT+DG
RM 3	SPVA+DG
RM 4	WT+BS
RM 5	SPVA+BS
RM 6	WT+SPVA+DG
RM 7	WT+SPVA+BS

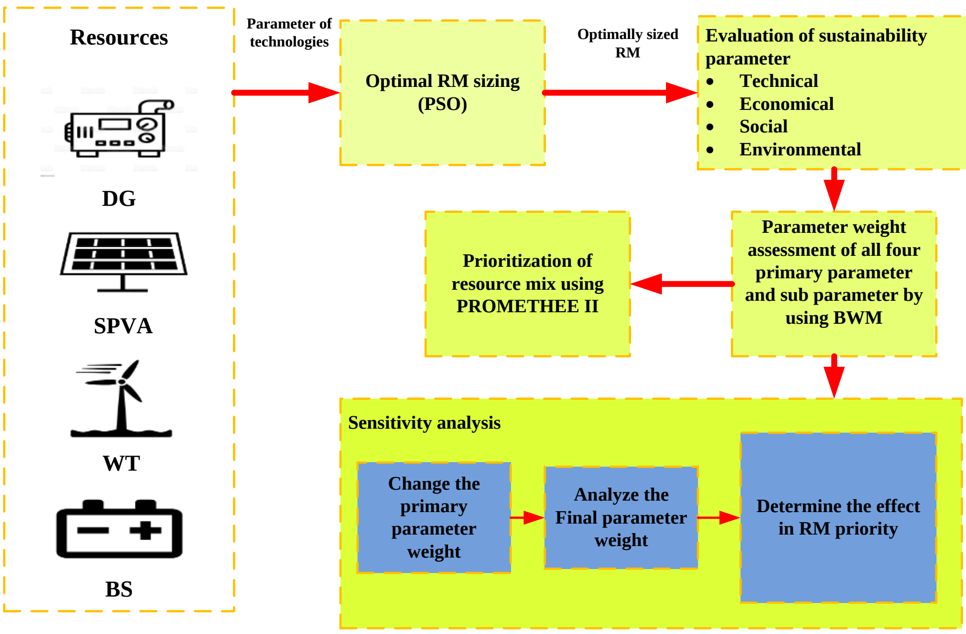


Fig. 1 Proposed methodology.

2.1.1 Solar Photovoltaic Array (SPVA)

The SPVA, utilizes solar light photons for the generation of electrical energy. The voltage and current of SPVA module are a function of solar irradiance (q) [5]. Thus, the output power of SPVA (O_{SPVA}) is dependent on solar irradiance. In this paper, Beta probability density function [5] is used for solar irradiance modeling.

$$O_{SPVA}(q) = N.v.i.\left[\frac{v_{mp} i_{mp}}{v_{oc} i_{sc}}\right] \tag{1}$$

The relation between voltage (v), current (i) and cell temperature (t_{SPVA}) is expressed as follows:

$$t_{SPVA} = t_a + q\left[\frac{N-20}{0.8}\right] \tag{2}$$

$$v = v_{oc} - k_v.t_{SPVA} \tag{3}$$

$$i = q[i_{sc} - k_i(t_{SPVA} - 25)] \tag{4}$$

where, v_{oc} presents open-circuit voltage, k_v presents voltage coefficient, v_{mp} presents voltage at max. power point, i_{sc} presents short circuit current, k_i presents current coefficient and i_{mp} presents current at max. power point.

2.1.2 Wind Turbine (WT)

The power generation from WT depends upon the wind speed (s) and turbine design [4]. The output power of WT can be expressed as follows [5]:

$$O_{WT}(s) = \begin{cases} a + b^m & \text{for } s_{cut\_in} \le s \le s_r \\ P_r & \text{for } s_r \le s \le s_{cut\_off} \\ 0 & \text{for } 0 \le s \le s_{cut\_in}, \text{ and } s \ge s_{cut\_off} \end{cases} \tag{5}$$

where, s_{cut_in}, s_{cut_off} and s_r presents cut-in, cut-off and rated speed of WT (m/s) and P_r presents rated power of WT unit (kWh).

In this paper, Weibull probability distribution [5] is used for the modeling of wind speed (s).

2.1.3 Diesel Generator (DG)

Diesel generators offer a dispatchable source of power generation that can be used alone or in conjunction with RES for supplying power to micro-grid. The operational cost (OPEX) of a diesel generator [26] is expressed by (6).

$$OPEX_{DG} = \sum_{k=1}^{n} (a + bP_k + cP_k^2) \tag{6}$$

where, $OPEX_{DG}$presents operational cost of DG ($/Hour), k presents number of DG units and a, b, and c are the cost coefficients.

2.1.4 Battery Storage (BS)

The study utilized [23] for BS modeling. This model overcomes the intermittent behavior of RES. This model uses the expected charging/ discharging value of the previous time segment for defining the present battery state of charge (SOC) [5]. The battery SOC is constrained by minimum and maximum permissible SOC values. The battery SOC is evaluated by using (7) [5]:

$$SOC^{t+1} = SOC^t \pm \frac{e^t_{charge/discharge}}{C_{BS}} \tag{7}$$

where, SOC^{t+1} presents battery SOC at (t+1)-th time segment, SOC^t presents battery SOC at t-th time segment, C_{BS} presents battery capacity and $e^t_{charge/discharge}$ presents charging and discharging energy from battery at t-th time segment.

2.2 Optimal Sizing of RM Using PSO

The objective function and constraints are as follows:

2.2.1 Objective Function

The objective function of optimal sizing is minimization of $LCOE$.

$$\min\ LCOE = \min\left[\frac{Life\ cycle\ cost\ (LCC)}{\sum_{n=1}^{n_{project}} E_n \big/ (1+r)^n}\right] \tag{8}$$

where, E_n, $n_{project}$, and r presents net energy supply during n-th year, project planning year and discount rate respectively.

The LCC presents the net present value (NPV) of total costs incurred over the project lifespan [4].

$$LCC = C_{Capital} + C_{OPEX} + C_{UL} + C_{rep} + C_{social} - C_{Salvage} \tag{9}$$

where, $C_{Capital}$, C_{OPEX}, C_{UL}, C_{rep}, C_{social} and $C_{Salvage}$ presents the NPV of capital cost, operational cost, unmet load cost, replacement cost, social cost and salvage cost of the component during the project lifespan.

2.2.2 Constraints

The optimal sizing problem is subjected to following constraints:

i. Reliability constraint:

$$UF_{unserved} \le UF_{\max} \tag{10}$$

where $UF_{Unserved}$ denotes the unmet fraction, which is the ratio of unserved load demand to the total load and $UF_{\max}$ denotes the maximum permissible limit of unmet friction.

ii. Component capacity constraints:

The upper and lower limit of capacity of system components pertaining to different RM are as follows:

$$C_{SPVA\_\min} \le C_{SPVA} \le C_{SPVA\_\max} \tag{11}$$

$$C_{WT\_\min} \le C_{WT} \le C_{WT\_\max} \tag{12}$$

$$C_{DG\_\min} \le C_{DG} \le C_{DG\_\max} \tag{13}$$

$$C_{BS\_\min} \le C_{BS} \le C_{BS\_\max} \tag{14}$$

where, $C_{SPVA\_\min}$, $C_{WT\_\min}$, $C_{DG\_\min}$, and $C_{BS\_\min}$ present minimum, and $C_{SPVA\_\max}$, $C_{WT\_\max}$, $C_{DG\_\max}$, and $C_{BS\_\max}$ maximum capacity of SPVA, WT, DG and BS components respectively.

2.2.3 Supply and Demand Balance Equilibrium

In all time segments, the balance between the demand and supplied power must be maintained. The total available power from various sources (P^t_{Total}) for t-th time segment is expressed as follows:

$$P^t_{Total} = P^t_{SPVA} + P^t_{WT} + P^t_{BS_{dis}} + P^t_{DG} \tag{15}$$

where, P^t_{Total} is total power supplied from all sources, P^t_{SPVA} is output power obtained from SPVA, P^t_{WT} is output power obtained from WT, $P^t_{BS_{dis}}$ is output power from BS during discharging mode, and P^t_{DG} is output power obtained from DG.

The power output from different sources specified in (15) is a function of the type of RM considered. For instance, if RM 2 is considered, then P^t_{SPVA} is taken equal to zero.

If P^t_{Total} is insufficient to supply the load, then unmet load (L^t_{Unmet}) in t-th time segment can be calculated as:

$$L^t_{Unmet} = L^t - P^t_{Total} \tag{16}$$

The charging and discharging of BS is a function of availability of power from RES and load demand. For t-th time segment, the BS charging/discharging mode are expressed as follows:
In case of surplus power from RES:

$$P^t_{BS_{ch}} = P^t_{SPVA} + P^t_{WT} - L^t \tag{17}$$

In case of deficit power from RES:

$$P^t_{BS_{dis}} = P^t_{SPVA} + P^t_{WT} - L^t \tag{18}$$

where, L^t is load over t-th time segment and $P^t_{BS_{dis}}$ is output power from BS during charging mode.

In this paper, component sizing for each RM is carried out using PSO [4].

2.3 Description of Sustainability Parameters

The term sustainability is basically used for developing a planning formulation in such a way so as to offer a viable economic, social, technical and environmental perspective [4]. In order to embody the concept of sustainability in RM selection, four main sustainability factors along with thirteen sub-factors parameters have been employed in this study. A description of sustainability parameters used in this work is presented in Fig. 2.

2.4 Application of MCDM Method for Prioritizing RM

The MCDM methods have been adopted in several works for technology prioritization. However, in this paper, the objective has been to focus on prioritizing RM rather than a particular technology. In this paper, the BWM has been used for parameter weight assessment and the PROMETHEE II method has been utilized for RM prioritization. The BWM is one of the newly developed and effective method amongst the class of weight assessment methods. BWM provides the capability of both qualitative and quantitative parameter weight assessment along with the choice preference of decision makers [33]. The PROMETHEE II method provides the complete alternative ranking based on real-life planning parameters [34]. The procedure of RM prioritization is illustrated in Fig. 3 and a detailed description of these two methods is provided in following sub-sections:

2.4.1 Best-Worst Method (BWM)

The BWM was first proposed by Rezaei in 2015 [35]. The BWM has the ability to solve different types of actual life-based decision problems. The BWM utilizes the pair-wise comparison of best and worst parameters [35]. The steps for implementation of BWM are as follows [36]:

i. Define the set of decision parameters.
ii. Define the best (highly important) and worst (least important) parameters.
iii. Define the preference of best parameter over other parameters by a number between 1 and 9.
iv. Define the preference of all other parameters over the worst parameter by a number between 1 and 9.
v. Determine the final weights of all parameters by expressing an optimization model. To assign parameter weight following two conditions need to be satisfied:

$$W_{best} / W_J = O_{best,J} \quad \text{and} \quad W_J / W_{worst} = O_{J,worst} \tag{19}$$

where, W_{best}, W_{worst}, and W_J present weights of best, worst and J-th parameter, respectively, and $Q_{best,J}$, $Q_{J,worst}$ present degree of preference of J-th parameter to best and worst parameter, respectively.

The objective function is to minimize difference of

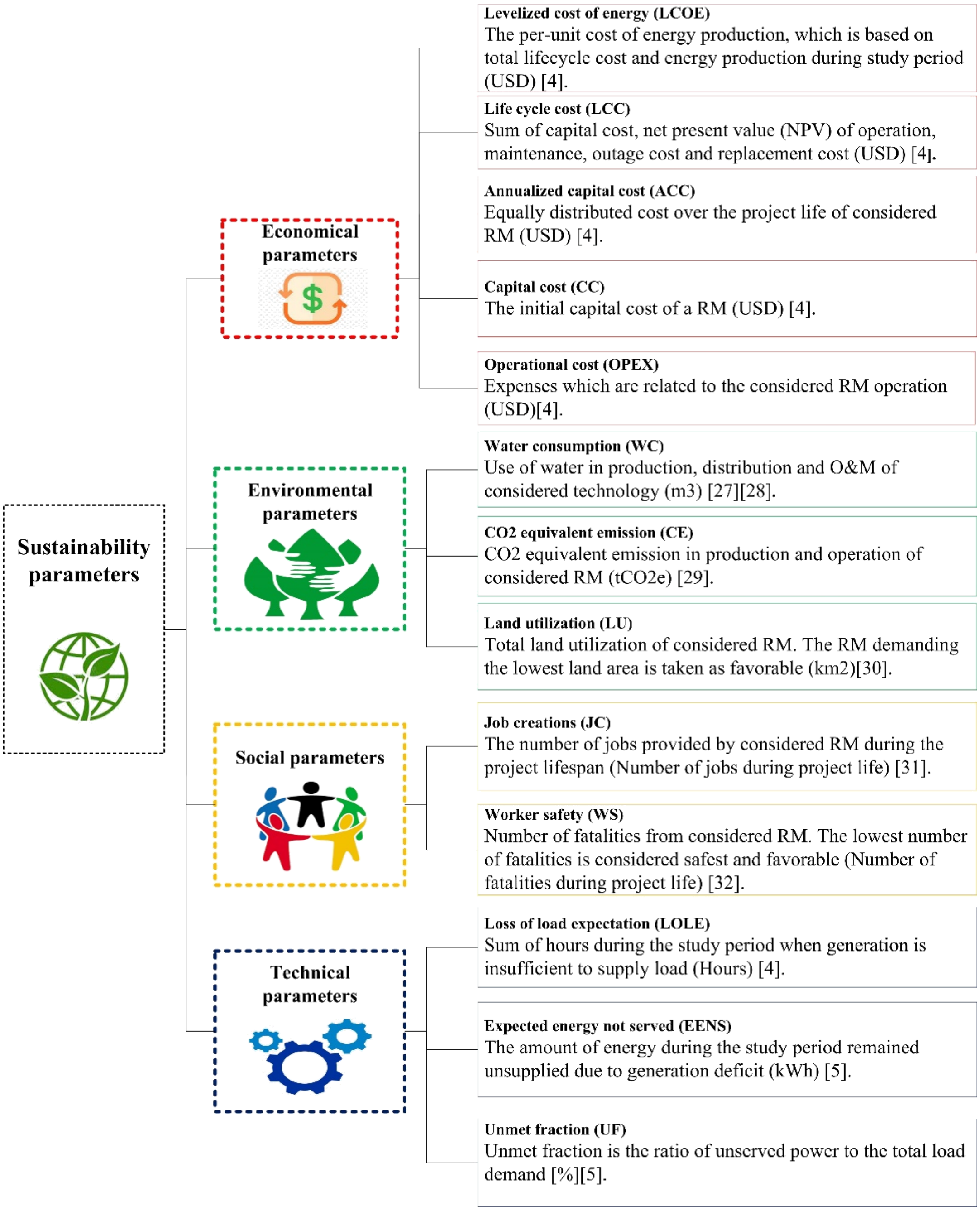


Fig. 2 Sustainability parameters.

$$|W_{best}/W_J - O_{best,J}| \quad \text{and} \quad |W_J/W_{worst} - O_{J,worst}| \qquad (20)$$

Based on these functions, minimum and maximum optimization models can be expressed as:

$$\min_J \max \left[|W_{best}/W_J - O_{best,J}|, \; |W_J/W_{worst} - O_{J,worst}| \right],$$
$$\text{s.t.} \quad \sum_J W_J = 1, \quad W_J \ge 0, \quad \text{for all } J \qquad (21)$$

The above problem can be expressed as follows:

$$\begin{aligned} &\min \ \zeta \\ &\text{s.t.} \ |W_{best}/W_J - O_{best,J}| \le \zeta \quad \forall J \\ &\quad\ \ |W_J/W_{worst} - O_{J,worst}| \le \zeta \quad \forall J \\ &\quad\ \ \sum_J W_J = 1, \ W_J \ge 0, \forall J \end{aligned} \qquad (22)$$

where, ζ used for consistency ratio analysis.

vi. By solving (22) all weights are obtained.

2.4.2 PROMETHEE II Method

PROMETHEE II method was proposed by Brans and

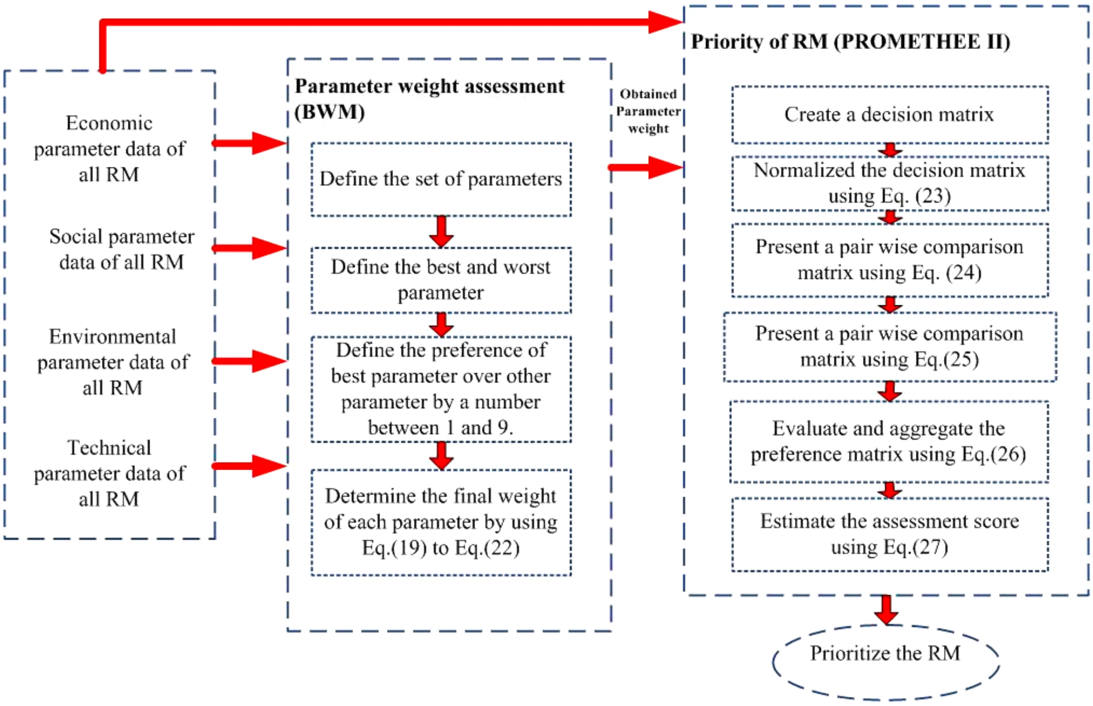


Fig. 3 Flowchart for execution of RM prioritization.

further modified by Vincke and Brans [34]. The PROMETHEE II is a more appropriate version where restricted alternative sets are to be analyzed for prioritization. This method prioritizes the alternatives based on their pairwise comparison [37]. The procedure for PROMETHEE II is as follows [37, 38]:

i. Create the decision matrix (a_{lj}) by using set of parameter (j = 1, 2, …, m) and set of alternatives (l =1,2,…n). Here, m and n denoted the number of parameters and alternatives.

ii. Normalize the decision matrix by using following expressions:

$$\bar{a}_{lj} = \begin{cases} \dfrac{[a_{lj} - \min(a_{lj})]}{[\max(a_{lj}) - \min(a_{lj})]}, & \text{for benefical parameter} \\ \dfrac{[\max(a_{lj}) - a_{lj}]}{[\max(a_{lj}) - \min(a_{lj})]}, & \text{for non-benefical parameter} \end{cases} \tag{23}$$

iii. Determine the variation by pairwise comparison between alternatives using (24)

$$D_j(x,y) = g_j(x) - g_j(y) \tag{24}$$

where, $D_j(x,y)$ presents the difference value of parameter j between the action x and y.

iv. Evaluate the preference function p_j, by using the following expressions:

$$P_j(x,y) = \begin{cases} 0, & \text{if } D_j(x,y) < 0 \\ D_j(x,y), & \text{if } D_j(x,y) > 0 \end{cases} \tag{25}$$

v. Evaluate the aggregated preference degree as follows:

$$\pi(x,y) = \frac{\sum_{j=1}^{m} w_j \; P_j(x,y)}{\sum_{j=1}^{m} w_j} \tag{26}$$

where, w_j is the weight of j-th parameter.

vi. Develop an aggregated preference matrix.

vii. Estimate the final net flow assessment score, by using positive outranking ($\varphi^{+}(A_l)$) and negative outranking ($\varphi^{-}(A_l)$) as follows:

$$\varphi(A_l) = \varphi^{+}(A_l) - \varphi^{-}(A_l) \tag{27}$$

viii. Finally, rank the alternative in decreasing order based on net flow ($\varphi(A_l)$) value.

3 Case Study: Thar Desert India

In this paper, a case study of an autonomous microgrid assumed to be located in the Thar desert, India has been presented. The geographical location of the Thar desert is shown in Fig. 4. The Thar desert is situated in the northwest part of India. Thar desert spreads over an area of around 200000 km^2 and stands at 9th position in area-wise ranking across the world amongst the subtropical desert group [39]. Thar desert's average solar irradiance is around 5.56 kWh/m^2/day and average wind speed is around 4.62 m/sec [4640 which clearly depicts its enormous potential for renewable power generation. Several solar and wind based power generation systems have been installed in the Thar region. Thus, in this paper, seven RM of four technologies namely SPVA, WT, DG and BS are prioritized for an autonomous micro-grid in Thar having a peak load of 70 kW. The load demand of four seasons *viz.* spring, summer, fall and winter is obtained from the

Fig. 4 Geographical location of Jaisalmer, India [41].

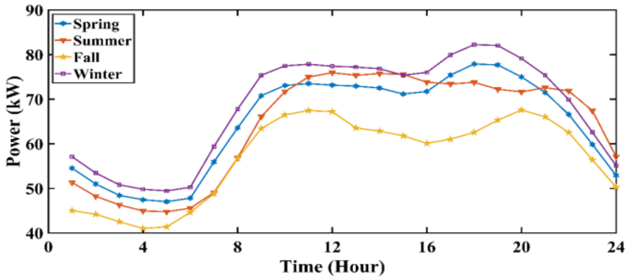


Fig. 5 Variation of load demand for four seasons [5].

Table 3 Economic specifications of resources.

Specification	SPVA [26, 42]	WT [42]	DG [42]	BS [42]	Converter [42]
Capital cost [$/kW]	630	1800	306	54	63
Maintenance cost	0.005 $/kWh	0.02 $/kWh	0.008 $/kWh	10 $	0 $/kWh
Fuel cost [$/liter]	-	-	0.94	-	-
Life	20 years	20 years	15000 hours	5 years	10 years

Table 4 Optimal component sizing for each RM.

RMs	DG [kW]	WT [kW]	SPVA [kW]	BS [kWh]
RM 1	100	-	-	-
RM 2	80	60	-	-
RM 3	80	-	90	-
RM 4	-	300	-	580.8
RM 5	-	-	315	1135.2
RM 6	80	60	60	-
RM 7	-	250	30	501.6

Table 5: Environmental and social specification of resources

Technology	CE [gCO_2e/kWh] [44, 45]	LU [km^2/kWh] [30]	WC [m^3/kWh] [44]	JC [No. of jobs] [31]	WS [Mortalities/TWh] [49]
SPVA	77	0.31	0.0005565	0.41 – 2.48 job/MW	0.019
WT	19.5	3.65	0.00002196	0.39 – 0.8 Job/MW	0.035
DG	733	0	0.00006	0.14 Job/GWh	0.0041
BS	138.9	0	0.752	0.01 Job/MWh	0

IEEE load profile and has been obtained from [5], as presented in Fig. 5.

4 Results and Discussion

The different stages involved in the evaluation of micro-grid planning such as optimal RM sizing, evaluation of RMs on sustainability parameters and finally RM prioritization have been discussed in Section 2. The simulation is performed on MATLAB R2016a software using AMD Ryzen 5 3500U with Radeon Vega Mobile GFX 2.10 GHz having 8 GB installed memory. The economic specifications used in the paper are presented in Table 3. The forced outage rate of generators is considered as 4% [5].

The results of optimal component sizing (discussed in Section 2) corresponding to different RM are presented in Table 4.

4.1 Analysis of Sustainability Characteristics

After determining the optimal component sizing for each RM, the evaluation is performed on the basis of sustainability parameters discussed in Section 2.3. The parameters for economic assessment have already been provided in Table 3. The specifications for the evaluation of environmental and social parameters are provided in Table 5.

A comprehensive analysis based on different sustainability parameters is carried out for different RM. Fig. 6(a) presents the economic parameters (ACC, LCOE, CC, OPEX, and LCC) for all seven RM.

Based on the above figures, following conclusions can be drawn:

i. As observed from Fig. 6(a), the analysis of economic parameters for all RMs exhibits that RM 5 (SPVA, BS) shows least value of LCOE, ACC, OPEX, and LCC. This can be accredited to low OPEX of the SPVA and BS technology. However, RM 5 shows the third largest CC. This clearly suggests that an RM cannot be turned down merely on the basis of high initial investment. A lifecycle evaluation can render better insight into economic

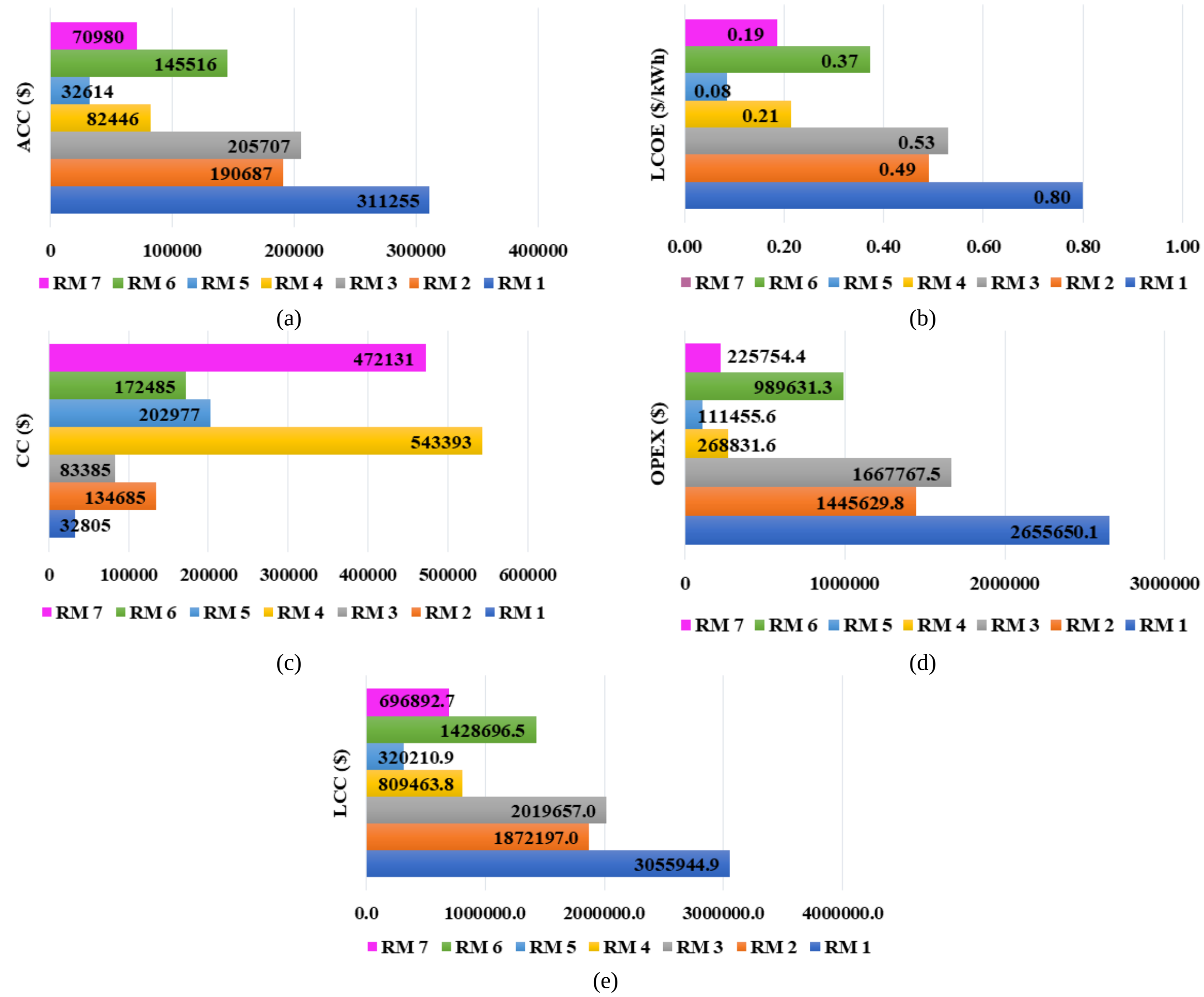


Fig. 6 a) ACC, b) LCOE, c) CC, d) OPEX, and d)LCC of all seven RMs.

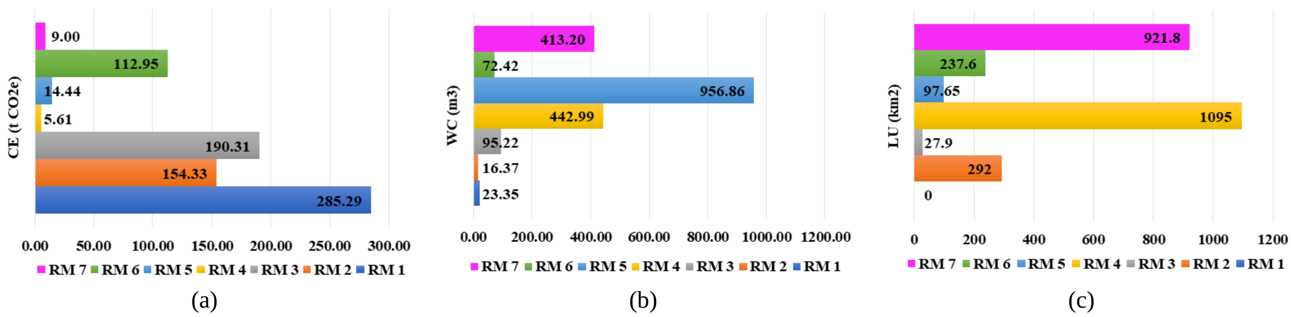
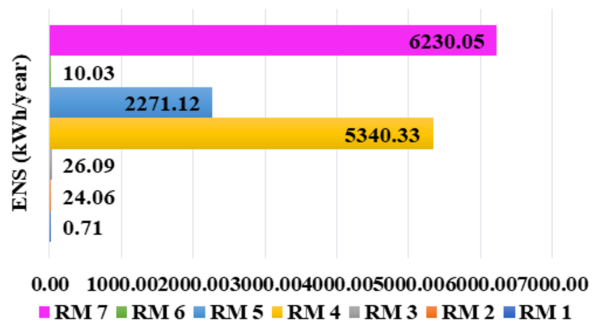


Fig. 7 a) CE, b) WC, and c) LU of all seven RMs.

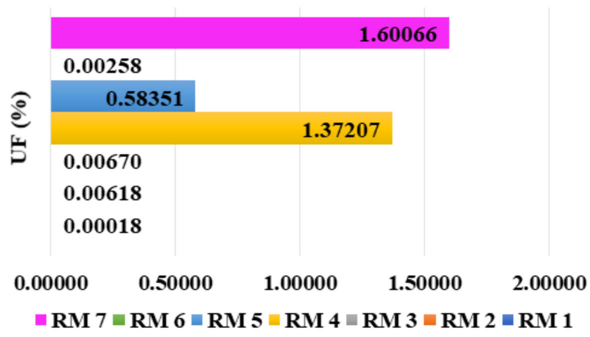
viability. This can be further established through the analysis of RM 1. RM 1 offers the lowest value of CC, due to low initial cost of DG units but exhibits the highest value of LCOE, ACC, OPEX and LCC due to high OPEX of DG.

ii. As observed from Fig. 7, the analysis of environmental parameters of different RMs reveals that RM 4 (WT, BS) offers least carbon eq. emission amongst all RMs. In contrast, RM 1 exhibits the highest carbon footprint due to the integration of DG. However, RM 1 requires least land utilization and second least water consumption among all RMs. Thus, on the environmental front, though the integration of DGs leads to poor air quality but wins on the parameters of land and water consumption.

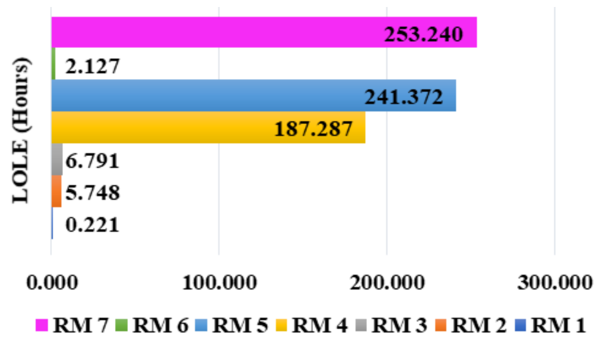
iii. As observed from Fig. 8, RM 1 shows lowest value of EENS, UF and LOLE, which makes RM 1 (DG only) the most reliable RM. This is obvious due to the fact that RM 1 consists only of DG which is a dispatchable source. In contrast, RM 7 (SPVA, WT and BS) indicates the least reliability, because of the intermittent nature of SPVA and WT



(a)

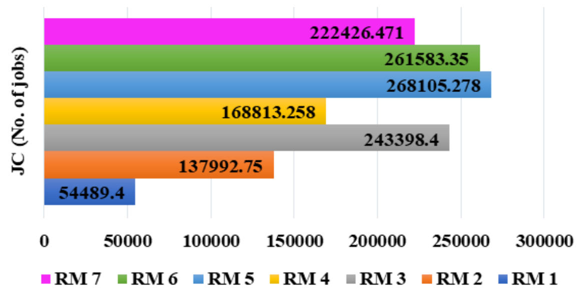


(b)

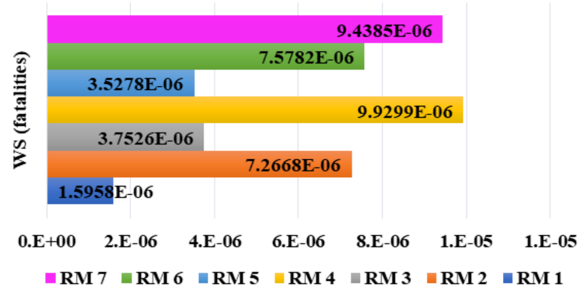


(c)

Fig. 8 a) EENS, b) UF, and c) LOLE of all seven RMs.



(a)



(b)

Fig. 9 a) JC and b) WS of all seven RMs.

units. This is suggestive of the fact that integration of RES may lead to a compromise in reliability standards and thus have to be analyzed judiciously.

iv. As observed from Fig. 9, the analysis of social parameters of RMs indicates that RM 5 creates the highest number of jobs. This is because RM 5 consists of large capacity of SPVA, which is the largest job-creating resource. The analysis of worker safety shows that RM 1 is the safest RM because RM 1 consists of only DG which has the lowest fatality rate amongst all considered resources.

4.2 Parameter Weight Evaluation Using BWM

In this paper, BWM has been used for parameter weight assessment. The method has been discussed in detail in Section 2.4.1. The weights of each parameter which are obtained based on the decision maker's priority of relative parameters are presented in Table 6.

It is evident from Table 6 that the economic parameter has the highest (0.5109) weight, as opposed to the social parameter with the least value of 0.06522. The local weights under the category of social primary parameter shows worker safety have a higher weight of 0.6667 as compared to job creation with 0.3333. Amongst the technical parameters, unmet friction has the greatest weight (0.6667) and LOLE (0.0833) has lowest weight. For environmental parameters, carbon emission has the highest weight of 0.5625 while for economic parameters, LCOE (0.4474) holds the highest weight.

The final weights are estimated by combining the individual primary and sub-parameters weights. The final weight of each sub-parameter is also presented in Table 6.

4.3 Sustainable RM Selection: PROMETHEE Method

Having determined the weights through BWM, the best sustainable RM amongst all seven alternatives is

Table 6 Parameter weight of all parameters and sub-parameters.

Primary parameter	Weight of primary parameter	Sub-parameter	Weights of sub-parameter	Final weights
Social parameter	0.065217391	WS	0.666667	0.043478283
		JC	0.333333	0.021739109
Technical parameter	0.141304348	UF	0.666666667	0.094202899
		EENS	0.25	0.035326087
		LOLE	0.083333333	0.011775362
Environmental parameter	0.282608696	CE	0.5625	0.158967391
		WC	0.3125	0.088315217
		LU	0.125	0.035326087
Economic parameter	0.510869565	LCOE	0.447368421	0.228546911
		LCC	0.263157895	0.134439359
		ACC	0.131578947	0.06721968
		CC	0.105263158	0.053775744
		OPEX	0.052631579	0.026887872

Table 7 Final RM ranking using PROMETHEE II method

Final ranking	RM 1	RM 2	RM 3	RM 4	RM 5	RM 6	RM 7
Rank	7	5	6	4	1	2	3

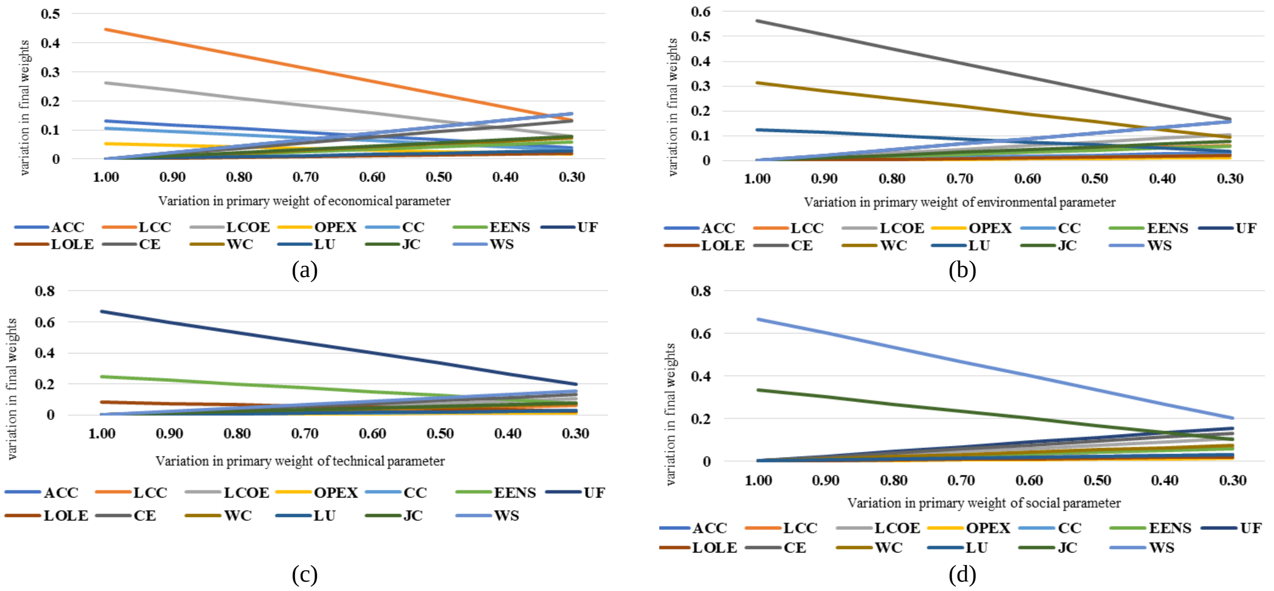


Fig. 10 Variation in primary weight of a) economic parameter, b) environmental parameter, c) technical parameter, and d) social parameter, all in percent.

obtained using PROMETHEE II method (discussed in Section 2.4.2). The ranking results obtained using PROMETHEE II method are presented in Table 7.

Table 7 depicts that, the RM 5 (SPVA and BS) provides the best RM for the considered location based on the sustainability parameters. It is also indicated that, RM 1 (DG only) has been assigned the lowest priority amongst all RMs.

4.4 Sensitivity Analysis

In Sections 4.2 and 4.3, the parameter weights and ranking of RMs are calculated based on the sustainability parameters. Since the parameter weight affects the alternative priority, it is essential to assess the effect of parameter weight variation on RM priority. Thus, in this paper, a sensitivity analysis is carried out by changing the primary weight of each parameter. In order to conduct the sensitivity analysis, the weight of one particular primary parameter is changed from 100 % to 30 %. Consequently, the weights of other primary parameters are increased/decreased. The summation of weights of different primary parameters should be equal to 1. In order to determine the subsequent effect on priority of RMs, PROMETHEE II is applied for each variation. The effect of change in weight of different primary parameters on final sub-parameter weights are presented in Fig. 10 and corresponding ranking variations are presented in Fig. 11.

Based on the sensitivity analyses, following conclusions can be drawn:

i. Fig. 11(a) presents the effect of variation of primary weight of economic parameters on RM ranking. It can be observed that when the primary weight of an

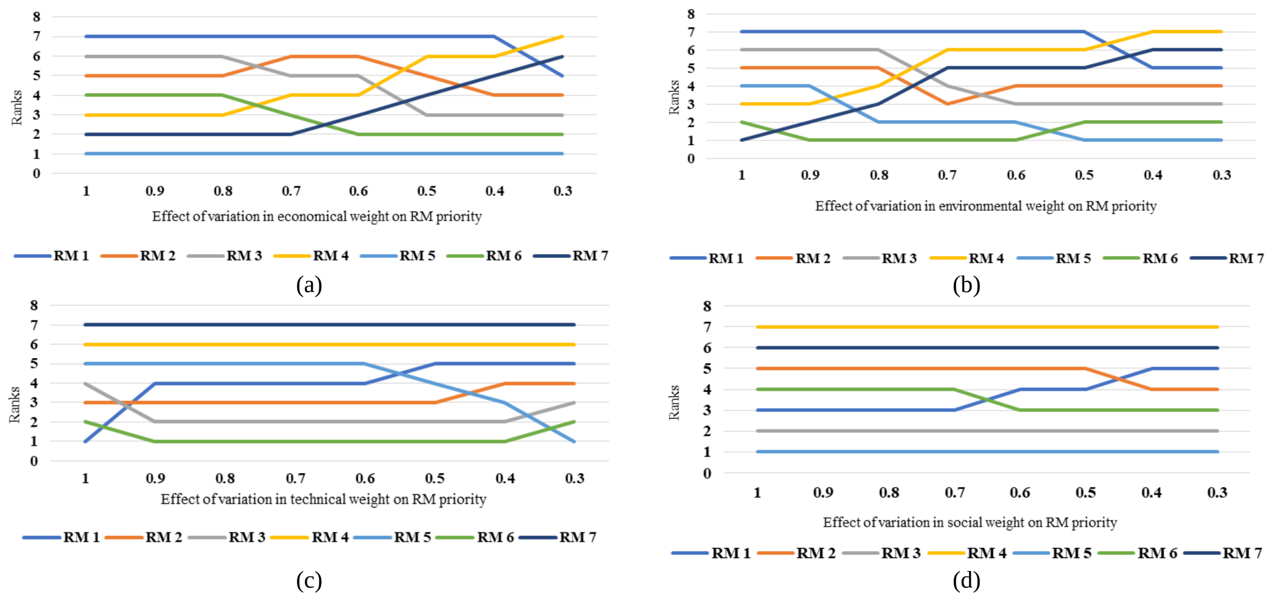


Fig. 11 Effect of variation in a) economic weight, b) environmental weight, c) technical weight, and d) social weight, on RM priority.

economic parameter is changed, RM 5 (SPVA and BS) option ranked first in all eight situations of economic weight variation.

ii. Fig. 11(b) presents the effect of variation of primary weight of environmental parameters on RM ranking. It can be observed that when the primary weight of environmental parameters is changed, RM 8 (SPVA, WT, BS) in one, RM 5 (SPVA, BS) in three and RM 4 (SPVA, WT, DG) in four scenarios scored first rank.

iii. Fig. 11(c) presents the effect of variation of primary weight of technical parameters on RM ranking. It can be observed that when the primary weight of a technical parameter is changed, RM 6 (SPVA, WT, DG) obtained first rank in six scenarios whereas RM 1 (DG only) and RM 5 (SPVA, WT) obtained first rank in one scenario each.

iv. Fig. 11(d) presents the effect of variation of primary weight of social parameter on RM ranking. It can be observed that when primary weight of social parameter is decreased from 1 to 0.2, RM 5 (SPVA and BS) option ranked first in all eight scenarios of social weight variation.

5 Conclusion

The selection of optimum and sustainable RM is essential for any project as the precise decision of RM selection improves the feasibility of the project. This paper presented an MCDM based planning formulation wherein seven RMs derived from a combination of two renewable resources: SPVA and WT, one leading energy storage technology: BS and/or one dispatchable generator: DG have been analysed. The analysis embedded four main sustainability parameters: economic (LCOE, CC, OPEX, ACC, LCC), environmental (carbon emission, water consumption, land utilization), social (job creation, worker safety) and technical (EENS, UF, LOLE) for the selection of best sustainable RM for the meteorological conditions corresponding to Thar desert, India. For MCDM analysis, the parameter weights are determined using BWM and RMs are prioritized using the PROMETHEE II method. A sensitivity analysis has also been performed by varying the weight of the primary parameter from 100 percent to 30 percent and analyzing its impact on RM ranking. The main conclusions based on this study are summarized as follows:

i. The final result of RM prioritization suggests that RM 5 (SPVA and BS) is the best sustainable RM for the selected location i.e., the Thar desert.
ii. Renewable energy source based RMs offer an economic and environment-friendly option despite their high capital costs.
iii. The MCDM method can facilitate the proper RM ranking considering multiple planning scenarios and parameters. This enables enhanced understanding about the choice of RM for a particular location.
iv. The sensitivity analysis reflects that the priority of RM is greatly influenced by variation in parameter weight.

The analysis presented in this paper can be further enriched by considering more resource combinations comprising different generation/storage technologies. In addition, more parameters can be incorporated to improve the sustainability assessment.

Intellectual Property

The authors confirm that they have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property.

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N. Thakkar: Conceptualization, Methodology, Analysis. **P. Paliwal:** Supervision, Verification.

Declaration of Competing Interest

The authors hereby confirm that the submitted manuscript is an original work and has not been published so far, is not under consideration for publication by any other journal and will not be submitted to any other journal until the decision will be made by this journal. All authors have approved the manuscript and agree with its submission to "Iranian Journal of Electrical and Electronic Engineering".

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