Optimized Use of Local Renewable Resources in Decentralized Hybrid Mode for Sustainable Energy Solution of Rural India

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"Statement of Originality"

I Shri Sayan Das registered on 13th March, 2020 do hereby declare that this thesis entitled" **Optimized Use of Local Renewable Resources in Decentralized Hybrid Mode for Sustainable Energy Solution of Rural India**" contains literature survey and original research work done by the undersigned candidate as part of Doctoral studies. All information in this thesis have been obtained and presented in accordance with existing academic rules and ethical conduct. I declare that, as required by these rules and conduct, I have fully cited and referred all materials and results that are not original to this work. I also declare that I have checked this thesis as per the "Policy on Anti Plagiarism, Jadavpur University, 2019", and the level of similarity as checked by iThenticate software is _____1___%.

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Dedicated to

My Parents

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Abstract

Primarily due to climate change and also due to resource depletion a global energy transition is imperative towards a low carbon economy. Increasing renewable share in the power mix is critical for this transition. However, renewable resources have several limitations as a substitute for existing fossil fuels. These renewable resources are generally dilute, intermittent and availability is location specific. Also, availability of these resources is not controllable according to the demand pattern. As a result, system installation for renewable power has to be optimized to assure uninterrupted power at minimum cost and environmental impact. The large-scale (of MW order) storage is not significantly used for such small scale off-grid energy systems. Hybridization of different locally available renewable resources may be an alternative solution to accommodate limitations due to capacity and intermittency of renewable resources.

India has widely varying topography with large variations of renewable resources at different locations both in type and available amount. Also, the socio-economic demography of India is widely varying with a large poor population. Providing reliable power at affordable cost to all Indians is a commitment of the government. Simultaneously, India is committed to net zero emission over a declared time schedule. To accommodate both the energy security of the poor Indians as well as switching over to a low-carbon economy, distributed hybrid renewable energy systems may be a suitable option. In this thesis, a systematic study of sustainability assessment of optimized solutions at different locations of India has been studied. The main objective is to explore sustainable solutions for reliable and clean power to poor populations of specifically remote locations of India. Studies have been carried out to assess an overall sustainability of such distributed renewable energy systems with several criteria like techno-economic, environmental and financial investment risk analysis. As these criteria do not converge to the same solution for a particular location, multi-criteria decision making is performed to decide the practically acceptable optimum solution for these locations. A general framework for Strengths-Weaknesses- Opportunities- Threats (SWOT) analysis of renewable power has been discussed before these studies to explore a sustainable policy guideline for future Indian renewable energy. Selection of the best possible location based on natural resources, social and economic factors using GIS data is also demonstrated. In addition to power several other energy services are also required for different locations of India. Studies are carried out to integrate other energy utilities with power using local renewable resources. India has a long coastline and severe ground water crisis. Desalination is the technology inevitably required for India. For a coastal location with shortage of consumable water,

integrating desalination with renewable power and sustainability assessment of it has also been done. Hydrogen is considered to be a very important energy carrier for the Indian economy. Generation and utilization of hydrogen in integrated energy systems is also explored. To match the gap between demand and supply in renewable energy systems, storage is required. Optimizing storage options including dispatch strategy is explored in one study. The overall study is conducted for seven different locations of India with some typical characteristics for each location. Brief objectives and obtained results for sustainability assessment of distributed hybrid renewable energy systems for rural India are as below:

- A comprehensive SWOT-more improved Hesitant Fuzzy multi-criteria decision-making analysis is required to identify these issues and their priorities for decentralized renewable HESs for Indian villages. The result shows the elimination of demand and supply gap by increasing energy efficiency and imposing taxes on the conventional energy sources are the highest and the lowest priority strategies for India.
- A methodology that integrates GIS with improved and efficient hesitant fuzzy linguistic multi-criteria decision-making to find suitable locations for developing decentralized hybrid energy systems at remote villages of Madhya Pradesh, India is developed. The integrated GIS-MCDM method ensures that Sailana, a remote village of Madhya Pradesh, India located at the western side of the state is the best location to develop the system.
- Techno-economically optimum decentralized hybrid energy system is explored for the remote rural villages of north-eastern hilly region of India, i.e., for the difficult Himalayan terrains of India. The techno-economic optimization shows that the Wind-hydro-DG-Li-ion is the economically optimal (cost of electricity-\$0.63/kWh) and the least emitting combination (481 kg/year) to meet the load demand of the area.
- Combined environmental impact assessment by life cycle assessment of energy systems with techno-economic optimization is done to explore better sustainable energy solutions. Study reported that the PV-DG-Li-ion is the best optimal solution with a cost of electricity-\$0.067/kWh, excess electricity-14.5% and environmental impact is 40.5–82% lesser for a remote village of the state of Rajasthan.
- Methodology to assess uncertainties in ROI for such systems is also studied. Study shows that the PV-DG-Battery system is the possible optimum solution for remote villages of Gujarat with a cost of electricity- \$0.21/kWh, a standard deviation of 0.07 for risk on investment and a moderate environmental impact.

- To improve the techno-economic performance of the energy systems integrated with storage systems, different electrochemical energy storage systems and mechanical storage devices integrated with HESs are compared under different dispatch strategies. Different dispatch and storage module analysis shows that the Zinc-Bromide storage integrated with PV-hydro-DG system is techno-economically optimum (cost of electricity- $0.197/kWh and net present cost- $362384) under 'Load Follow' dispatch strategy for a remote village of Bihar state.
- Comparison between green hydrogen with other conventional storage systems in terms of techno-economic performance factors and risk in ROI is studied for a remote village of Sunderban, West Bengal. The PV-Wind-DG-Li-ion is optimal (cost of electricity- $0.159/kWh, net present cost- $424568, renewable fraction- 96.5% and standard deviation- 0.45%).
- Techno-economic feasibility of different desalination units powered by decentralized hybrid energy systems are also explored. The decentralized hybrid energy system integrated RO-desalination unit is most cost effective (cost of water- $4.57/L) and least emitting for a village of Tamilnadu.

Title of the Thesis

Optimized Use of Local Renewable Resources in Decentralized Hybrid Mode for Sustainable Energy Solution of Rural India

Contents

List of Figures

.

List of Tables

Symbols and Abbreviations

Abbreviations

AC	Alternating current (amp)
ADS	Automatic desalination system
AHP	Analytic Hierarchy Process
Al	Aluminium
ANP	Analytic Neural Process
AP	Arithmetic Progression
ARAS	Additive Ratio Assessment
BIC	Bayesian Information criteria
CAMPA	Compensatory Afforestation Fund Management and Planning Authority
CAPEX	Capital expenditure
CC	Cycle charging
CD	Combined dispatch
CEA	Central electricity authority
CES	Conventional Energy Source
CFL	Compact fluorescent lamp
CI	Consistency Index
CO_2	Carbon dioxide
COE	Cost of electricity
COP	Cost of production
COW	Cost of water
CR	Consistency Ratio
CRF	Capital recovery factor
CS	Capacity Shortage
Cu	Copper
DC	Direct current
DDUGJY	Deen Dayal Upadhyaya Gram Jyoti Yojana
DG	Diesel Generator
EE	Excess electricity
EI	Environmental impact
ELECTRE	ELimination Et Choice Translating REality
F	Fuzzy
FC	Fuel cell
F_C	Fuel consumption
FLTS	Fuzzy linguistic term set
FU	Functional unit
GA	Genetic Algorithm
GE	Generated electricity
GHG	Green House Gas
GIS	Geographic information system
GM	Geometric mean
GOI	Government of India

H	Hydrogen
HDI	Human development index
HES	Hybrid Energy System
HFL	Hesitant Fuzzy Linguistic
HFLTS	Hesitant Fuzzy Linguistic Term Set
HOMER	Hybrid Optimization of Multiple Electric Renewable
HT	Hydrogen tank
Hydro	Hydropower turbine
IEA	International Energy Agency
IPCC	International Panel on Climate Change
IPPDS	Ideal Predictive Power Dispatch Strategy
JNNSM	Jawaharlal Nehru National Solar Mission
L.H.V.	Lower heating value (MJ/kg)
LA	Lead acid
LAB	Lead-acid Battery
LAF	Lead acid flow battery
LCA	Life cycle assessment
LF	Load following
Li-ion	Lithium-ion Battery
LPSP	Loss of power Supply Probability
MCDM	Multi criteria decision-making
MCS	Monte Carlo simulation
MED	Multi-Effective Desalination
MNRE	Ministry of New and Renewable Energy
MOP	Ministry of Power
MPPT	Magnetic power point tracking
MSF	Multi-Stage Flash
N.V.	Nominal Voltage (volt)
NEPAD	New Partnership for Africa's Development
NIS	Negative Ideal Solution
NO_2	Nitrogen di-oxide
NOCT	Nominal optimum cell temperature
NPC	Net Present Cost (US$)
NREL	National Renewable Energy Laboratory
O & M	Cost of system’s operation and maintenance ($/kW/y)
OPEX	Operational expenditure
OWA	Ordered weighted Average
PHES	Pumped hydro energy storage
PIS	Positive Ideal Solution
PM	Particulate matter
PROMETHEE	Preference Ranking Organization method for Enrichment of Evaluations
PV	Photovoltaic
R&D	Research and development

RCI	Relative closeness Index
RER	Renewable Energy Resources
RES	Renewable energy share
RF	Renewable fraction (%)
RI	Random Index
RO	Reverse osmosis
ROI	Return on investment
ROSA	Reverse Osmosis system analysis
SAUBHAGYA	Pradhan Mantri Sahaj Bijli Har Ghar Yojana
SDG	Sustainable development goal
SO	Strength, opportunity
SO_2	Sulphur di-Oxide
SOC	State of charge (%)
SW	Strength, weakness
SWOT	Strength, Weakness, Opportunity. Threat
T&D	Transmission and distribution
TE	Technical efficiency
TFN	Triangular Fuzzy Number
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
UHC	Unburned hydro carbon
UL	Unmet Load
UN	United Nations
UNGA	United Nations General Assembly
USGS	United States Geological Survey
VIKOR	VIekriterijumsko KOmpromisno Rangiranje
VR	Vanadium Redox battery
W	Wind
WASPAS	Weighted Aggregated Sum-Product Assessment
WECS	Wind Energy Conversion system
WHO	World Health Organization
WO	Weakness, opportunity
WT	Weakness, threats
ZB	Zinc Bromide battery

Symbols

A	area of the wind turbine blade (m^2)
Ah	area of the Hydro (m^2)
c	Storage capacity ratio
C emission	Penalty cost for carbon emission (costs are in $/year)
C_{annual_t}	Annualized cost ($)
C_{cap}	Capital cost (US$)

$C_{capital}$	Capital cost (US$)
C_{CO}	Penalty for emission of CO (costs are in $/ton)
C_{CO2}	Retribution cost of emitted CO2 (US$/ton)
C_{cs}	Retribution cost for shortage of capacity (US$/ year)
Cdiesel	Diesel cost (costs are in $/litre)
C_{fuel}	Fuel cost (US$/L)
CI	Initial expenditure (costs are in $)
Ci	Relative closeness
$\check{c}_i$	matrix
$\mathbf{C_{min}}$	Minimum cost function (US$)
C_{NO2}	Penalty cost of emitted NO_2 (US$/ton)
$C_{O\&M}$	Operation and maintenance cost (US$)
$C_{o\&m, fixed}$	constant cost of O&M (US$/year)
$C_{o\&m, other}$	alternate cost of O&M (US$/year)
Cp	Betz constant
$C_{p,H}$	Performance coefficient of Hydro
C_{PM}	Penalty for emission of PM (costs are in $/ton)
C_{PM}	Retribution cost of emitted PM (US$/ton)
Cr	Replacement cost (costs are in $)
C_{rep}	Replacement cost (US$)
$C_{salvage}$	Salvage cost (US$)
C_{SO2}	Penalty cost of emitted SO_2 (US$/ton)
C_{ta}	Total annualized cost (US$)
C_{UHC}	Penalty for emission of unburned hydro carbon (costs are in $/ton)
$E_{battery}$	Power of storage modules (kWh)
$E_{deficit}$	Total energy deficit per year (kWh)
E_{Hydro}	Energy generation from Hydro (kWh)
E_{non_ren}	Non-renewable energy served (kWh)
env (H_s)	HFLTS envelope
E_S	Total energy served (kWh)
Eserve	Everyday load (kWh)
Et	Electricity generation in a year
f	Nominal inflation rate (%)
F	Consumed fuel
$F_{0, DG}$	Coefficient of fuel curve intercept (Units/h/kW)
$F_{1, DG}$	Fuel curve slope (Units/h/kW)
FF	fill factor of the system
F_{PV}	Derating factor (%)
Ft	Fuel expenditures in a year
G	solar irradiance (W/m^2)

g	Gravitational acceleration (m/s^2)
G0	standard irradiance of the solar (W/m^2)
G_h	Grammar used in the linguistic term set (LTS) S
G_{ref}	Solar standard irradiation (kW per sq. m)
G_T	Daily solar radiation (W per sq. m per day)
$G_{t, NOCT}$	Solar irradiation at NOCT (kW per sq. m)
$G_{T,STC}$	Solar radiation at standard situation (W per sq. m per day)
H	net head of the system (m)
$h_p(y)$	function
H_s	subset of S
i	Real rate of yearly interest
i'	Nominal interest rate
Isc	short circuit current (amp)
It	Investment expenditure in a year
k	Storage constant
K_T	Clearness Index
M_{CO}	Annual emission of CO (kg/year)
M_{CO2}	Annual emission of CO2 (kg/year)
M_{NO2}	Annual emission of NO2 (kg/year)
M_{PM}	Annual emission of PM (kg/year)
M_{SO2}	Annual emission of SO2 (kg/year)
M_{SO2}	per year unit amount SO_2 release
M_t	O&M expenditure in a year
M_t	Per year O&M
M_{UHC}	Annual emission of UHC (kg/year)
M_{UHC}	per year unit amount UHC release
n	Project lifetime
n	Project overall lifetime
N_{batt}	Minimum battery requirement
NC	Component capacity (kW)
N_C	module capacity (kW)
N_{PV}	Number of solar modules
N_{WT}	Total number of wind turbines
P	Subset within the range of
P	power developed by hydro turbine (kW)
P_b (t)	storage device power
P_{conv}	Power of inverter
$P_{Converter}$	Converter power (kW)
$P_{deficit}$	Load deficit (kW)
P_{DG}	Actual consumed power

P_{Hydro}	power produced by hydro kinetic component (kW)
$P_i(t)$	Input power of inverter
P_{load}	Total electrical energy required
Pmax	maximum power of the PV module (kW)
P_{max}	Overall energy delivered by wind module (kW)
$P_o(t)$	Output power of inverter
P_{Peak}	Peak time power
P_{PV}	PV module's output power in kW
$P_{PV,STC}$	PV module's output power in standard temperature condition in kW
$Pr\ (t)$	Rated power of wind turbine
$P_{surplus}$	Surplus electric power (kW)
P_W	power produced by wind turbine (kW)
Q	discharge rate of water (m^3/s)
Q	State of Charge
R	Discount rate
$ř_i$	row number
rij	Normalized matrix
RS	series resistance of the module (ohm)
S	$\{s_o, \ldots, s_g\}$ is the set of linguistic terms
$S_{ll.}$	domain of the expressions generated by G_h
T	temperature of the PV system in (K)
t	Time in seconds
T0	standardized temperature of the PV system in (K)
T_0	Solar module standardized temperature in (K)
T_a	Ambient temperature. (°C)
$T_{a,\ NOCT}$	PV module's ambient temperature at NOCT condition. (°C)
T_C	PV module's cell temperature (°C)
$T_{C,\ NOCT}$	PV module's cell temperature at NOCT condition (°C)
$T_{failure}$	Total electricity failure
T_{ref}	Temperature of of PV module in standard condition in °C
T_{STC}	PV module's standard cell temperature (°C)
T_{total}	Total hours of operation
U_L	Transfer coefficient in W/sq.m-K
V	Wind speed (m/s)
V_{anem}	Wind velocity at anemometer height (m per s)
V_B	Voltage of the battery (Volt)
$Vc\text{-}_{0ut}$	Cut off wind speed at hub height (m/s)

V_{c-in}	Cut -in wind speed at hub height (m/s)
$V_{hub-height}$	Wind velocity at specific hub height (m per s)
vij	Weighted normalized matrix
VOC	open circuit voltage (Volt)
V_{rw}	Rated wind velocity at hub height (m per s)
V_t	Wind velocity at any instant t (m per s)
wij	Weightage value
xij	Element of matrix
Y	Set
Y_{DG}	Predicted consumed power
Y_{dg}	Nominal power of DG
Y_{PV}	Rated capacity of the PV module
Z_{anem}	anemometer height in m
Z_{hub}	Hub height (m)

Greek letters

α	Solar absorptance
α_P	Temperature coefficient of solar component
α, β, λ	exponential component for the nonlinear effects of PV system
Δ	Interval
η	System's efficiency
η_C	Electrical conversion efficiency of the PV system
$\eta_{charging}$	Charging efficiency
$\eta_{discharging}$	Discharge efficiency
η_{Hydro}	Hydro system's efficiency
η_{inv}	Inverter efficiency
η_{PV}	efficiency of the PV system
η_t	Total efficiency
ηinv	inverter efficiency
ρ	water density (kg/m^3)
ρ_w	density of the water (kg/m^3)
σ	air density (kg/m^3)
σ	Self-discharge percentage
τ	Transmittance of the PV module
$\tau\alpha$	Absorption transmittance of PV module

Chapter-1

Introduction

1.1 Background:

Ever-increasing world population, high living standard with rapid industrialization and urbanization is increasing global energy demand (Malik et al., 2022). According to the World Bank and International Energy Agency (IEA) reports, the global installed power capacity may double for the developing countries in the next forty years to meet the growing electricity demand (Pandiyan et al., 2022). Till date the energy utility services are mostly dominated by fossil fuel-based energy systems (approximately 60% of the total energy share) (Singer & Peterson, 2011). However, these conventional resources are finite in quantity and also depleting fast, emit greenhouse gases (GHGs) which causes global warming (Chauhan & Saini, 2015). To address the climate change impact, countries under the United Nations (UNs) have signed an agreement to restrict the global temperature rise by 1.5ºC from the pre-industrial level. It is supported by the International Panel on Climate Change (IPCC) by organizing Conferences of Party (COPs) (Paris agreement, 2015).

Access to reliable electricity increases productivity and provides economic development for society. Affordable, clean and reliable electricity to all is the aim of one of the Sustainable Development Goals (SDGs), i.e., SDG 7, proposed by the UNs for improving the global human development index (HDI) (Elkadragy et al., 2021). According to IEA's second report over 1.3 billion people from remote villages are unable to access the reliable grid electricity due to techno-economic constraints (Pandiyan et al., 2022). Therefore, countries are recently having more emphasis on increasing the energy share from locally available renewable energy resources. Renewable energy generation not only reduces the carbon emission but also improves energy access services promoting sustainable development in remote villages (Malik et al., 2022). It is expected that the emission from the energy sector will be slashed up to 11% if renewable energy share is raised to 45% by 2030 (Thambi et al., 2018). Though these renewable energy resources are possible options for the future, these have several limitations too, say, dilution in energy density, intermittency, uneven distribution and need for significant capital investment. "Hybridization", i.e., integrating different renewable energy resources supported by suitable storage modules and/or other back-up systems (like diesel generator (DG) sets) is one of the possible options to overcome these limitations. For electrification of these villages, extension of the national grid to these remote villages may not be cost-effective

(Fadaee & Radzi, 2012). Decentralized hybrid energy system (HES) is one of the possible options to address this issue.

India, a major developing country with 1.4 billion population with an installed capacity of 425 GW is one of the major generators and consumers of electricity (Harish et al., 2022). High population density with rapid industrialization is continuously increasing the energy demand of India too (Khan et al., 2021) . The maximum amount of the Indian energy is still catered through fossil fuels (Murugaperumal & Raj, 2019). Figure 1.1 shows the share of different energy resources for India (Narayanan, 2021). According to another study, 70% of the Indian population are rural of which only 18% of the total population have reliable access to electricity (Chiller, 2017). Considering this, the Government of India (GOI) has adopted different national mission schemes. Jawaharlal Nehru National Solar Mission (JNNSM) was initiated in 2010. It targeted to develop 175 GW of installed capacity from renewable energy resources by 2022 (Government of India, 2022). Subsequently, the Indian government decided to achieve 100% electrification in India through the Saubhagya scheme, announced in 2017 (Department of Agriculture & Farmers Welfare, 2021). However, many households of the rural areas at remote locations still do not have the access to reliable and consistent power due to higher cost and several other technological issues (Government of India, 2021b). To provide “Power to all” through “Indian Vision 2040” in line with the global decarbonization mission, the Indian government is shifting its focus to develop decentralized HESs using locally available renewable energy resources in remote areas (Government of India, 2017). Renewable energy resources such as solar, wind, biomass and small hydro are abundantly available all over the country, though intensities of these resources vary widely at different locations (Bhanja & Roychowdhury, 2023).

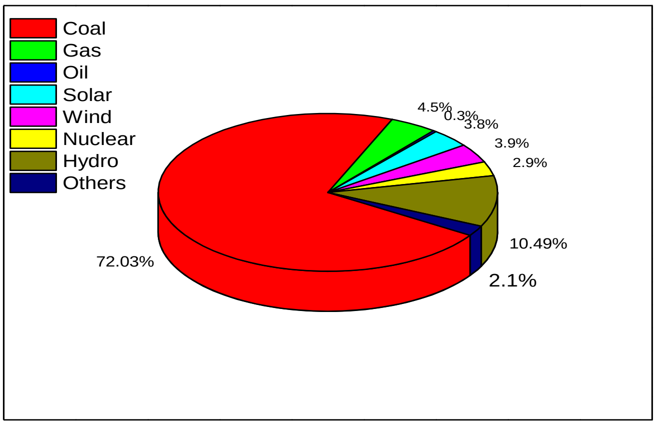


Fig. 1.1: Share of different energy resources in India (Narayanan, 2021)

1.2 Decentralized HES and announced policies in India:

With a mission of rural electrification in the country for steady low-carbon economic growth, the Indian government has set a priority to develop decentralized HESs for remote villages. Several policies and schemes are announced by the Indian Government to increase the renewable share in the utility energy mix. Different national programs are introduced for this purpose. “Solar Parks Scheme” aims to achieve 40 GW capacity by developing solar parks and ultra-mega solar power projects by the year 2024, “PM-KUSUM scheme” targets to install 10,000 MW decentralized grid-connected solar power plants and 20 MW standalone solar powered agricultural pump for enhancing energy and water security in rural villages (Ministry of New and Renewable Energy, 2022). Subsequently “Solar Rooftop Scheme”, “Off-grid solar scheme”, “Green energy Corridor”, “Wind-Solar hybridization scheme” are also announced to support and increase the development of the decentralized HES using local renewable resources (Ministry of New and Renewable Energy, 2022). The Compensatory Afforestation Fund Management and Planning Authority (CAMPA) (*CAMPA*, 2009) and the National Afforestation Program (NAP) (GOI, 2019) are declared by the Government for supporting the green India mission (GOI, 2012). To shape the decarbonization narrative for India by encouraging green energy as a significant component of transformational change the Indian Government announced “Panchamrit” a climate action program of India (Jnu-eiacp, 2022). This plan is to be implemented in five different phases. Simultaneously the government has the ambition to achieve a net zero emissions by 2070. Lifestyle for Environment (LiFE) scheme (Jnu-eiacp, 2022) is being pursued for it. These schemes are in line with the green energy mission of India. Decentralized HES is now an Indian priority for supplying reliable, clean and affordable energy in rural areas. It may help to achieve better energy security of rural India which is essential for steady economic development of the country.

Different organizations are engaged in energy strategy planning as well as implementation in India. These organizations work in collaboration to successfully implement national mission programs. Steady increase in energy demand has increased the gap between demand and supply though the % gap decreased in the country as shown in Fig. 1.2 (NITI Aayog, 2022b). This needs to be addressed for the future energy security of the country. New energy policies with proper prioritization is a major challenge for the country towards achieving relevant SDGs (NITI Aayog, 2022a). Adoption of appropriate energy strategies is a complex process for successful energy transition towards better sustainability (Government of India, 2016).

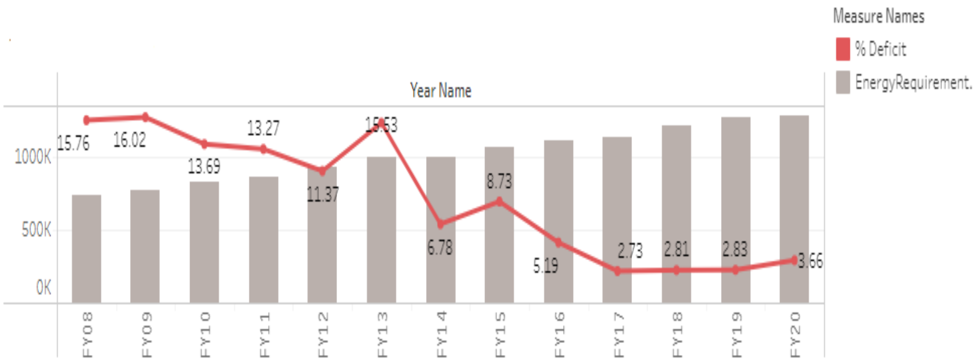


Fig. 1.2: India's energy demand-supply scenario ((NITI Aayog, 2022b)

1.3 Importance of location selection:

India is a large country with wide geographical variations. In India solar, wind and biomass are the most abundantly available renewable energy resources though their availability varies widely at different locations of the country. According to the Government of India Report of Renewable 2019 (Fabiani et al, 2019) the wind and solar power contribute about 28% and 55% of the total national renewable energy share respectively.

Developing hybrid energy systems have a few challenges too, say, habitat loss, land degradation, visual intrusion, noise pollution etc. (Yin et al., 2017). However, to maximize the energy generation by simultaneously minimizing these adverse impacts, identification of suitable location to establish the decentralized HES is essential (Yun-Na et al., 2013). Locations with maximum solar radiation and wind velocity may not always be the best location for developing the HES (Tavana et al., 2017). Other factors, say, economic profitability, meteorological requirement, social challenges and environmental concern need to be addressed for finding the most preferred site (Saraswat et al., 2021). The selection of sites based on different evaluation criteria is a difficult but necessary decision-making process.

1.4 Importance of techno-economic optimization:

Rural areas of India are often rich in different renewable resources such as solar, wind, biomass, micro hydro etc. It offers the opportunity to develop hybrid distributed energy systems for better low carbon energy security (Mokhtara et al., 2021; X. Wang et al., 2018). Hybrid energy system using clean energy resources with suitable storage modules and a back-up system is a sustainable solution for energy transition (Li et al., 2022). 'Sustainable Development' integrates economic, environment and social perspectives (United Nations Department of Economic and Social Affairs, 2019). Figure 1.3 shows the factors included for it.

Fig. 1.3: Sustainability factors ((United Nations Department of Economic and Social Affairs, 2019)

Cost-effectiveness, power quality and reliability are the significant challenges for developing the optimal sustainable decentralized hybrid energy system (Yadav et al., 2021). Objective functions and constraints are to be defined for such optimization (Ray et al., 2017). The definitive optimization algorithms are generally used for this purpose. Techno-economic optimization of different energy combinations for several remote villages of India may be an interesting study (Ray et al., 2018).

1.5 Environmental Impact Assessment:

For overall sustainability assessment, detailed environmental impact assessment is essential. The Life cycle assessment (LCA) is the standard global methodology to comprehensively assess this impact. For new and emerging technologies, LCA is even more critical to assess the possible future environmental impacts to determine its overall sustainability.

1.6 Risk assessment:

Risk in return on investment (ROI) is one of the major challenges for any new technology with uncertainties. Due to different uncertainties (Aldersey-Williams & Rubert, 2019) future risk in ROI for new emerging energy technologies is a critical concern for the investors (Lazard, 2021). For traditional power projects the cost of electricity (COE) is easier to estimate and hence lesser risk on ROI is involved (Aldersey-Williams & Rubert, 2019). Most of the renewable energy technologies are non-dispatchable and intermittent which causes a mismatch between energy demand and supply. It leads to uncertainties in COE. The storage and back-up system are required for an uninterrupted power supply (Tran & Smith, 2017) . Energy performance uncertainties, technical limitations associated with system's lifetimes, scalability, unavailability of skilled man-power and many other factors create uncertainties in the overall performance of new renewable power generation systems causing risk in ROI (Akarsu & Serdar Genç, 2022).

1.7 Multi-criteria-decision making:

The multi criteria decision-making (MCDM) process is the procedure of deciding the most feasible optimal solution among the alternatives presented according to many decision-making criteria (Munier et al., 2019; Rojas-zerpa & Yusta, 2015). The decision-making process has to be done for issues with multiple options with following steps: define the problem; identify the alternatives; determine the criteria and the weights of the criteria; resolve the decision; testing and implementing the decision (Dagtekin et al., 2022). The process of decision-making becomes more complex if the number of alternatives increases and the weights of the criteria varies. In this respect, the MCDM is considered. This process prioritizes the alternatives by applying an analytical approach on the basis of criteria weights given by the decision makers (Dagtekin et al., 2022).

To optimize the overall sustainability of a system several factors need to be simultaneously optimized. The optimization of each performance factor may not converge into a single solution (Ali et al., 2020). This demands for the MCDM methods to be used for deciding an acceptable optimal sustainable solution (Alao et al., 2020).

1.8 Storage system and dispatch strategy:

HES has a few limitations, say., intermittency, demand-supply mismatch, network constraints and power quality issues (Moore & Shabani, 2016). Integrating two or more renewable energy resources into a HES decreases the intermittency, though not fully. Energy Storage System (ESS) is required on top of it for a better match between demand and supply (Buonomano et al., 2018). These ESSs also support demand load shifting, PV curtailment reduction, demand peak shaving etc. (Le et al., 2023). In addition, small capacity back-up systems such as diesel generator (DG) sets may also be useful to integrate with the HES for more reliability (Kilic & Altun, 2022).

On the other hand, a proper energy management plan is required for optimal coordination of all components towards achieving adequate renewable fraction (RF) (Chaurasia et al., 2022). Dispatch strategy analysis is important for obtaining a reliable and cost-effective energy combination (Kushwaha & Bhattacharjee, 2022).

1.9 Techno-economic and risk analysis of green hydrogen storage:

The decentralized system also generates excess electricity (EE) which may be used to produce hydrogen through water electrolysis for a better sustainability (Amin et al., 2023). This hydrogen can be used as a storage (Akarsu & Serdar Genç, 2022) or as a clean fuel for society. The techno-economic optimization with risk in ROI assessment is important for such new emerging technologies to understand the overall sustainability of the proposed storage system.

1.10 Secondary utilities:

Besides providing electricity to the households HES is also capable of meeting several other energy utility services. Analyzing sustainability of HES with multiple energy utility services is also important to identify future potential systems, catering to some specific local needs.

1.11 Organization of the thesis

This PhD work explores feasibility and optimum solution for overall sustainability of decentralized hybrid energy systems, specifically for India. India has widely varied geographical features including high mountains, long coast, plain land, deep forest and even desert. There are also widely varying demography and socio-economic conditions. There exist remote locations mostly with poor people with limited options for their livelihood. Access to electricity for most of these poor populations is limited and it affects their social development. In line with the commitment of the Government of India for power to all and more renewable share in the power mix, introducing hybrid renewable energy systems for these populations is useful. However, it needs national priority of policies, proper site selection as well as adopting systems with optimum overall sustainability for best implementation of these missions. This thesis explores the overall chain of this process in eleven chapters as described below.

Chapter 1: Introduction

In this section, motivation and background of the research, the detailed study and the necessity of this research is illustrated.

Chapter 2: Literature Review

A detailed literature review is presented in this chapter to show the present state of the art research in this field. The research gaps are also identified. The research objectives are accordingly discussed in this chapter.

Chapter 3: Determination and prioritization of energy strategies using SWOT-HFL-AHP-TOPSIS method

In this chapter the strengths, weaknesses, opportunities and threats of the decided energy policies for India are determined. Depending on the determined energy strategies it is prioritized using the decision-making approach.

Chapter 4: GIS and MCDM approach for selecting an optimal site to develop a decentralized HES

In this chapter, different evaluation criteria which are determined by using the GIS technology are evaluated through MCDM methods. The study helps to decide an optimal site for developing a decentralized HES.

Chapter 5: Techno-economic optimization of different energy combination

In this chapter techno-economic optimization integrated with MCDM methods help to obtain an acceptable optimal solution for the decided study area.

Chapter 6: Techno-economically optimal and environmentally benign decentralized HES

In this chapter, the environmental impact assessment by LCA is performed along with the techno-economic optimization and MCDM approach to find a sustainable energy combination for the decided location.

Chapter 7: Techno-economic with least financial risk and environment-friendly decentralized HES

This chapter includes risk analysis, environmental impact assessment, techno-economic optimization and MCDM methods to obtain an acceptable optimal energy combination.

Chapter 8: Comparison of different storage systems and dispatch strategies

The chapter shows technically efficient and cost-effective energy combinations by performing techno-economic optimization for different storage modules integrated with energy systems. In this chapter three different dispatch strategies are also analyzed for obtaining an optimal system.

Chapter 9: Techno-economic with least risk hydrogen storage system

In this chapter, the techno-economic and risk in ROI analysis is performed for the green hydrogen with respect to the electrochemical energy storage systems to understand the proposed system's sustainability.

Chapter 10: Techno-economic analysis of desalination unit supported by decentralized HES

This chapter performs a techno-economic optimization to obtain an optimal desalination unit supported by decentralized HES as an additional required energy service for that location.

Chapter 11: Conclusion and future works

This chapter discusses the conclusions obtained from the above-mentioned studies. Possible future works are also discussed in this chapter.

Chapter- 2

Literature Review

2.1 Introduction:

A state-of-the-art literature review is carried out to update the published knowledge and identify the research gap for optimum use of renewable resources in decentralized hybrid systems for overall energy service sustainability of rural India. The literature review includes different aspects for this purpose as described in subsections below.

2.2 Energy strategy determination and prioritization:

Deciding proper strategies and determining the right priorities of these at the national level for better resource utilization helps to supply efficient, reliable and affordable electricity to all (Akçaba & Eminer, 2022). Ideal energy strategies should include both short and long-term goals on the basis of capabilities and potentials of different regions under different constraints, such as budgetary limitations, technological restrictions, conflicting geo-political objectives etc (Solangi et al., 2019). This is a multi-criteria decision-making process integrating techno-economic, ecological and social issues for an overall sustainable development (Ioannou et al., 2017).

Strengths, weaknesses, opportunities and threats (SWOT) technique is considered as an appropriate method to properly determine the energy strategies. SWOT techniques are widely used in different strategic planning and management studies. In Table 2.1 the application of SWOT technique in different areas including the energy sector are discussed.

Table 2.1: Implementation of SWOT method in different sectors

Authors (year)	Method used	Objective of the study	Conclusions
Sahu et al., (2023)	SWOT-Block-chain technology (BCT)-Strategies and Threats (STRATH)	To seek the expert's opinion to embrace various strategies and elevate the fertility of the BCT	Eight threats were found under cause group and eight opportunities were found under effect groups
Nilashi et al., (2023)	SWOT method	To analyse the SDGs by giving the emphasis on COVID-19 crisis impact on Malaysia	The study demonstrated that in the post-crisis time, the citizens ratio under poverty could grow up more

			than the current value
Amirshenava & Osanloo, (2022)	SWOT method	To evaluate the post mining land use (PMLU) vulnerabilities and proposed an appropriate solution to assess the mined land suitability	Non-renewable base PMLU option achieved the best strategic option
Meza et al., (2022)	SWOT method	To analyse the challenges and opportunities that LNG market of Qatar will face in future	Due to the strengths Qatar would continue to be a reliable, economic and responsive source of LNG supplier
Hosseini et al., (2021)	SWOT method	To assess sustainable development of ecotourism in Iran	The results showed that establishing ecotourism centre in the region had greatest impact
Gkoltsiou & Mougiakou, (2021)	SWOT method	To visualize the stakeholder's ideas regarding landscape types of the islands	The planning of development consensus between experts and stakeholders regarding the landscape types were the priority
Schmidt & Leitner, (2021)	SWOT method	To find the strengths, weaknesses, opportunities and threats of the hybrid energy systems	It showed that the cost-effectiveness was the strength of PV-wind hybrid energy system
Jing & Tao, (2021)	SWOT method	To analyse the fit between recent situation of the enterprise with the future development goal	To achieve the vision company must change to the expansive development strategy mode from the conservative progressive mode

Besides determining the strategies, prioritizing those determined strategies by integrating different MCDM approaches with this SWOT method is essential for an effective implementation of these policies. Table 2.2 shows some literature that used SWOT-MCDM approaches for strategy development and prioritization.

Table 2.2: SWOT-MCDM approach for strategy determination and prioritization

Authors (year)	Method used	Objective of the study	Conclusions
Rahimirad & Sadabadi, (2023)	SWOT-MCDM	To determine strategies and prioritize it for developing future hydrogen roadmap of Iran	The determination of the role of green hydrogen technologies in energy policy design was getting the highest priority.
Akçaba & Eminer, (2022)	SWOT-Analytical network process (ANP)-Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (FTOPSIS)	Decide energy strategies for Cyprus	Establishing interconnection to the mainland was of the highest priority
Safder et al., (2022)	SWOT-FTOPSIS	To evaluate the Pakistan's energy sector for preventing future energy crisis	To develop the nation as an energy hub it need to use the geostrategic location with the support of regional administration.
Büyüközkan et al., (2021)	SWOT-Fuzzy analytic hierarchy process-Measurement of Alternatives and Ranking according to COmpromise Solution (MARCOS)	To analyse and determine different digital transformation strategies for Turkey	The study reported that to adopt a business model focusing on differentiated digital customer's experience were getting the highest priority

2.3 Suitable location selection for developing decentralized HESs:

The suitable location selection is highly recommended for the best performance of the decentralized HESs. To select a site for a decentralized HES project, geographic information system (GIS) may be an economic and efficient tool. Integration of MCDM with this GIS may be able to solve the critical challenge of acceptable optimal real-life decision-making by ranking different criteria and evaluating different possible alternatives. It deals with vast geographical information data and helps to select a feasible optimal site for the project. The methods used in previous analysis are discussed in Table 2.3.

Table 2.3: GIS-MCDM approach for location selection

Authors (year)	Proposed methodology	Objective of the study	Output
Shao et al., (2023)	GIS-MCDM	Tidal current power plant site selection for China	Among all the alternatives, alternative in Weihai region of China was the best possible option
Asadi et al., (2023)	GIS-AHP-Support vector regression (SVR)	Wind firm site selection for Iran	Eastern Iran had wind potential with flat terrain can able to generate endless source of wind energy
Aghaloo et al., (2023)	GIS-Best worst Method (BWM)-FMCDM	Site selection for developing solar-wind hybrid energy system in Bangladesh	Chittagong was the best possible location for developing the project
Demir et al., (2023)	GIS-AHP	Site selection for solar power plant at Turkey	Izmir was the best possible location in turkey for developing the site
Wang et al., (2022)	GIS-AHP-TOPSIS	For finding suitable location to develop integrated energy stations	Tianjin region China was the optimal location
Gil-García et al., (2022)	GIS-FMCDM	For selecting offshore wind farm location for Gulf of Marine	Most suitable location produced 1GW wind power with a cost of electricity (COE)-$100.4/MWh
Nagababu et al., (2022)	GIS-FAHP-TOPSIS	To select location for micro-level wind farms in India	Study showed that Gujrat and Tamilnadu were the most suitable locations for developing the farms
Rios & Duarte, (2021)	GIS-MCDM	Selecting site for large solar projects in Peru	Southern, north and the coastal regions were the highly adequate locations
Saraswat et al., (2021)	GIS-MCDM	Feasible location selection in India for solar and wind farms	Study reported that Rajasthan was the most suitable location

			for developing the project
Cunden et al., (2020)	GIS-AHP-Weighted linear combination (WLC)	To find a suitable wind farm location in Mauritius	Western region of the country was suitable to develop the farm
Konstantinos et al., (2019)	GIS-AHP-TOPSIS	Suitable site selection for wind farm in Greece	North-west region showed the best site for developing the farm
Merrouni et al., (2018)	GIS-AHP	Large scale solar site selection in Morocco	19% of the region was highly suitable to design the solar station

2.4 Linguistic Uncertainty:

In complex decision-making problems, decision information along with the performance of alternatives under different criteria, is difficult to collect directly. It demands to be evaluated in a subjective manner by experts. As human thinking is vague, decision-makers tend to use linguistic terms for expressing their evaluation. In such conditions, dealing with these issues MCDM methods are now extended and combined with the linguistic approaches. In these methods linguistic models are used to represent the decision information. Recent complex analysis considers these linguistic approaches integrated with MCDM for overcoming the limitation of uncertainties. A set of reviewed literature is discussed in Table 2.4 that used linguistic uncertainties in their studies.

Table 2.4: Linguistic uncertainty and MCDM methods

Authors (years)	**Methods used**	**Objective of the study**	**Case study**	**Outcome**
Aydoğan & Ozkir, (2024)	Fermatean fuzy set-TOPSIS-Stepwise weight assessment ratio analysis (SWARA)	To evaluate the reliability and flexibility of the data and rank them	Performance of research University and the production of fresh orange juice facility of Turkey were considered	Adana is decided as a most suitable option

Chai et al., (2023)	Intuitionistic fuzzy set-Triangular fuzzy number-interval-valued fuzzy number-cumulative prospect theory	To asses sustainable supply chain determination	Supply chain management for e-bike were considered for a case study	Cost and the A3 are best criteria and alternative respectively to supply sustainable e-bike
Yang et al., (2023)	AHP-q-rung orthopair linguistic partition Bonferroni mean	To evaluate and rank the available alternative low carbon fuels	The study was performed for the transport sector	e-fuel and e-biofuel are the two top ranked alternative fuels
Yu et al., (2022)	Interval 2 tuple linguistic-similarity aggregation method-simplified Best Worst method-Proximity Indexed value	To decide Off-shore wind firm site-selection	Shandong coast, China	Location Laizhou Dongying is optimal
Wang et al., (2022)	Hesitant fuzzy linguistic term sets-Best-worst method-TOPSIS	To assess the risk for identify and eliminate a system failure	The study considered gear grinding machine with the worm grinding wheels	Asynchronous rotation is the most influential risk that causes unquantified processing
Wu et al., (2022)	Probabilistic linguistic VIKOR	To evaluate the feasibility of the proposed method	The personal evaluation was considered as a case study	The method has wide application as it carried both subjective and quantitative analysis
Liu et al., (2019)	Best-worst method-alternative queuing method	To evaluate the sustainable supplier	As a case study watch suppliers were evaluated	The proposed model is more capable to capture the uncertainty and ambiguity of the decision makers
Quan et al., (2018)	Interval-valued intuitionistic uncertain linguistic sets-extended MULTIMOORA	To rank the green supply chain systems	The study was demonstrated with a data of real-estate	The proposed method reflect the expert's fuzziness and ambiguity more accurately

2.5 Techno-Economic optimization of decentralized HESs:

Techno-economic decentralized hybrid energy systems using locally available renewable resources are the possible sustainable solutions. However, there are several constraints for developing an economic energy combination for supplying an interrupted power. Obtaining an optimized solution for such energy combinations is an engineering challenge based on different objectives of optimization and constraints imposed on it. Reliable power supply at minimum economy and environmental hazards may be an important issue. To design a feasible power plant for meeting the local load demand through locally available renewable resources optimization is to be performed (Jana & De, 2015). A review of literature that performed techno-economic optimization for obtaining an optimal solution are discussed in Table 2.5.

Table 2.5: Techno-economic optimization for decentralized HES

Authors (year)	Location of study	Energy modules	Objective	Methods used	Conclusions
Heydari et al., (2023)	Danish town, Sonderborg	Solar-wind-DG-battery	To minimize COE and loss of power supply probability (LPSP) and maximize renewable energy source (RES)	Energy management strategy, Taguchi method, Moth flame multi-objective optimization and fuzzy MCDM	Scenario I- COE- $0.224/kWh, LPSP- 0.754 Scenario II- COE- $0.313/kWh, LPSP- 0.612 Scenario III- COE- $0.368/kWh, LPSP- 0.547
Kumar et al., (2023)	Eastern India	Solar-micro-hydro-biomass-battery	To optimize COE	Random forest technique and FO-JAYA	Best COE - $3.933/kWh
Abdelhady, (2023)	Egypt	Solar-wind-biogas generator	To optimize COE and net present cost (NPC)	Hybrid Optimization of Multiple Energy Resources (HOMER Pro®)	NPC – k$ 388 COE - ¢2.1 /kWh
Kumar & Channi, (2022)	Punjab, India	Solar-biomass-battery	To optimize COE, NPC, initial capital cost, operating cost, energy generation and renewable fraction	HOMER Pro® and TOPSIS	COE- $0.362/kWh, NPC - $21087 and emission – 0.232 kg/yr

Malik et al., (2022)	Western Himalayan region	Solar-biomass	To optimize COE and emission	HOMER Pro®	COE-$0.099/kWh and emission saved by 27.8 Mt CO_2/yr
Li et al., (2022)	China	Solar-biogas-DG-battery	To optimize COE, NPC and emission	HOMER Pro ®	COE-$0.24/kWh, NPC-$1808992 and emission saved by 1297174 kg CO_2/yr
Ali et al., (2021)	Pakistan	Solar-battery-DG	To optimize COE	HOMER Pro ®	COE-$0.072/kWh
Khan et al., (2021a)	Village of Lucknow, Uttar Pradesh, India	Solar-wind-DG-battery	To optimize COE and NPC	HOMER Pro ®	COE-$0.179/kWh and NPC - $31,439 for optimum solution
Pal & Bhattacharjee, (2020)	West Bengal, India	Solar-biogas generator-battery	To optimize LPSP, COE and total net present value (TNPV)	PSO	TNPV reduce by 54.4% with COE Rs. 9.88/kWh
Sarkar et al., (2019)	India	Solar-wind-biogas generator-storage	To optimize PB and internal rate of return	HOMER Pro ®, LabVIEW	PB is in between 4-5 years with IRR of 23% for the optimal solution
Jayachandran & Ravi, (2019)	India	Solar-DG-Battery	To optimize load sharing and output voltage control	Droop control with Model predictive voltage control (MPVC)	Improved power balance and load sharing in hybrid energy system unit
Nag & Sarkar, (2018)	Jharkhand, India	Solar-wind-hydrokinetic-bioenergy	To optimize COE and total generation	HOMER Pro ®	COE-$0.356/kWh and total generation was 133045 kWh/yr

Ansong et al., (2017)	Ghana	Solar-fuel-cell-DG-battery	To optimize COE	HOMER Pro ®	Study showed that the combination of PV-fuel cell-battery-DG was economic (COE-\$0.22/kWh)
Salehin et al., (2016)	Kutubdia Island, Bangladesh	Solar-wind-DG	To optimize COE, payback period and CO_2 emission	HOMER Pro ® and RETScreen	Study showed that the combination of Solar-DG system was optimal (COE-\$0.353/kWh, payback period – 11.2 years and emission-54.3tCO_2 eq.
Kolhe et al., (2015)	Sri Lanka	Solar-wind-battery-DG	To perform techno-economic optimization	HOMER Pro ®	Study reported that the combination of Solar-DG-wind-battery was optimal (COE-\$0.3/kWh)

2.6 Environmental impact assessment of decentralized HESs:

For sustainability including techno-economic optimality the energy combination should be environment-friendly. Detailed environmental impact assessment through LCA helps to obtain an overall sustainability of the systems. Table 2.6 shows summary of literature review that reported LCA used in the energy sector.

Table 2.6: Environmental impact assessment of energy systems

Authors (year)	Location	System for LCA	Outcome of the study
Huber et al., (2023)	Belgium	Solar and battery system	Midpoint impact assessment was done
Jiao & Månsson, (2023)	Sweden	Different storage modules	Cradle to gate GHG emission reported that the combination of Pumped-hydro-Lithium-ion (Li-ion)-flywheel has the least GHG impact
Ge et al., (2023)	China	solar-heat pump-gas turbine	LCA is used to analyse the overall GHG emission
Vijay et al., (2022)	Rajasthan, India	Biomass-based power generation	GHG emission analysis for the system
Aberilla et al., (2020)	Philippines	Solar-wind-DG-battery	Midpoint impact assessment is performed through LCA
Banacloche et al., (2020)	Tunisia	Concentrated solar power (CSP)-biomass	Midpoint impact assessment of the combination was performed
Nsafon et al., (2020)	Cameroon	Solar-wind-DG	Only CO_2 emission was assessed
Wang et al., (2019)	Hong Kong	Solar-wind-Lead-acid (LA)-DG	Midpoint impact assessment was performed using LCA
You et al., (2017)	Indonesia	Palm biomass gasification-based energy system	GHG emission analysis was carried out through LCA
Benton et al., (2017)	USA	DG module	LCA was performed for the DG set
Akinyele & Rayudu, (2016)	Gusau, Nigeria	Life-cycle cost (LCC) and the life cycle impact (LCI) was evaluated for different energy combinations	Study showed that the combination of solar-DG system was economic with less CO_2 emission (LCC-$425,500 and LCI-5178 kg CO_2 eq.)

2.7 Financial risk assessment of decentralized HESs:

Considering the need of obtaining sustainable energy combinations along with techno-economic optimization and environmental impact assessment, risk in ROI analysis is essential. Summary of previous literature that performed risk analysis in the energy sector is discussed in Table 2.7.

Table 2.7: Risk analysis in energy sector

Authors (year)	Method used	Objective of the study	Outcome
Hinestroza-Olascuaga et al., (2023)	Monte Carlo Simulation (MCS)	Lowering the investment risk in energy	Improved the TNPV of the energy system
Abud et al., (2023)	MCS	Uncertainty analysis of power quality improvement	Improved the reliability of the power quality for electrical network with DG
Moradi et al., (2022)	GAMS optimization in CPLEX solver	Risk measurement at conditional value for power to gas system	Mitigated the risk and showed the standard deviation by 0.2
Uwineza et al., (2021)	HOMER Pro®, MCS	To improve the financial risk in COE for Popova Island	Solar-wind-DG-battery system was most economic with least risk system
Prabatha et al., (2021)	Multi-objective optimization, Taguchi and MCS	To analyse different uncertainty levels	With high uncertainty moderate renewable fraction system was the most suitable

2.8 Multi-criteria decision-making methods used in decentralized HESs:

The performance assessment factors such as economic optimization, environmental impact assessment and financial risk analysis may not converge to a single solution. Thus, MCDM approach may need to be integrated finally to obtain an acceptable sustainable optimal solution. Different MCDM techniques are used in energy fields to decide an optimal solution. Table 2.8 shows the summary of literature review that used MCDM methods for deciding the solution.

Table 2.8: MCDM methods in decentralized HESs:

Authors (year)	Location	Used MCDM techniques	Objective	Obtain solution
Rivero-iglesias et al., (2023)	Spain	AHP-Fuzzy Interface system	To assess the environmental risk of the alternative energy systems for Spain	Study showed that the Solar energy system was the best optimal solution
Yazdani et al., (2023)	Shiraz, Iran	AHP + TOPSIS+ Entropy weighting method	To decide a feasible optimal solution	Study reported that solar-gas turbine-fuel cell-electrolyzer-hydrogen tank-battery was the

				most favourable solution
Ge et al., (2023)	Malawi	CRITIC+PROMETHEE II	To decide an optimal energy combination	Study reported that Solar-biogas generator was the optimal solution with a COE-$0.095/kWh
Sarkodie et al., (2022)	Ghana	CRITIC+ MOORA+ TOPSIS+ CORPAS	To find the most suitable energy resources	Study showed that the hydro resource was the best option for the location
Yousef et al., (2022)	Sudan	WASPAS+ WSMWPM+ TOPSIS	To decide an optimal energy combination for the location	Study showed that the combination of Solar-750kW DG and battery system was the best optimal solution with a COE-$0.224/kWh
Albawab et al., (2020)	UAE	Extended SWARA+ARAS	To decide a feasible storage system	According to the study thermal energy storage system was the best optimal storage for the hybrid system
Yuan et al., (2020)	Zhejiang, China	Mahalanobis-Taguchi-Gram-Schmidt-φs transformation-grey correlation	To decide a hybrid energy system for industrial park	Solar and wind integrated energy system was an optimal solution for the location
Rehman et al., (2022)	Pakistan	Fuzzy full consistency method-F-VIKOR-Fuzzy Quality function deployment	To identify the risk mitigation strategies	Study reported that improvement of coordination between the organisations and the maximizing the energy efficiency potential gained the highest priority
Singh et al., (2020)	India	Monarch butterfly-TOPSIS	To optimize the economy for distributed energy resources	Optimum solution reduced the loss by 78.6%

Diemuodeke et al., (2019)	Nigeria	HOMER+TOPSIS	Techno-economic and emission optimization for different energy combinations	Combination of Solar-wind-battery-DG was economic $0.893/kWh

2.9 Storage systems and dispatch strategies for decentralized HESs:

To improve the techno-economic performance of the hybrid energy systems different storage modules are analysed under various energy control strategies. Different storage modules such as electrochemical storage systems, mechanical storage systems, super capacitors, air storage systems are integrated with the hybrid energy systems for the techno-economic analysis. Several dispatch strategies are also analysed in previous published literature to determine more efficient energy systems. Table 2.9 shows a summary of literature review that analysed these topics.

Table 2.9: Dispatch strategies and storage modules for decentralized HESs

Authors (year)	Considered storages and dispatch strategies	Solution
Bazdar et al., (2023)	Adiabatic compressed air energy storage system (A-CAES) and improved energy management operation strategies (I-EMOS)	I-EMOS integrated A-CAES showed the best performance over traditional EMOS.
Pelosi et al., (2023)	Compared flywheel-Li-ion battery with reversible solid oxide cell (rSOC)-Li-ion storage system	Study showed that flywheel-Li-ion was an optimal storage option over rSOC-Li-ion system with a cost of storage (COS)- €110/MWh
Shezan et al., (2022)	Load following (LF), cycle charging (CC), combined dispatch (CD), generator order (GO), HOMER predictive dispatch (PS) approaches were analysed	Simulation showed that the LF strategy was the best dispatch strategy for HES
Dahash et al., (2021)	Exergoeconomic assessment of thermal energy storage (TES) integrated with renewable heating system was performed	Study showed that the low-temperature renewable-based district heating was economic as compared to high-temperature district heating in integration with TES
Ramesh & Saini, (2020)	LF, CC and CD dispatch strategies were analysed for LA and Li-ion storage systems	The study showed that the Li-ion storage system under CD dispatch strategy was the best

		solution with COE-$0.158/kWh and NPC- $7,11,980
Kumar & Saini, (2020)	LA, Li-ion and Nickel Iron (NI) battery storage systems were compared	According to the study Solar-Biogas generator with NI storage module showed a better result under CC strategy with COE-$0.238/kWh.
Kaabeche & Bakelli, (2019)	Techno-economic optimization under different LPSP method was performed for the hybrid system for three different storage systems, say, LA, Li-ion and Nickel-Cadmium (NI-CD)	Study showed that NI-CD storage integrated with hybrid system was economic
Eteiba et al., (2018)	Three different energy storage systems integrated with solar-biomass system, say, Flooded LA, Lithium Ferro Phosphate (LFP) and Nickel-Iron (Ni-FE) were evaluated	Study showed that the Solar-biomass-NI-FE system was the optimal configuration
Comodi et al., (2017)	Li-ion, TES, Phase change material, compressed air energy storage and Liquid air energy storage were analysed for cooling applications	Li-ion energy storage system was economic as compared to other techniques.
Crespo Del Granado et al., (2016)	Compared thermal energy storage system with VRF integrated with renewable energy resources and DG system	Flow battery is more economic and optimal as compared to thermal energy storage

2.10 Hydrogen storage system with decentralized HESs:

In small capacity hybrid energy systems, the mostly used electro-chemical energy storages such as LA and Li-ion batteries have several limitations. Costs of these storage modules are high, unable to use full charge therefore less efficient, and slow charging rate etc (Poullikkas, 2013). Subsequently the decentralized hybrid energy systems generate surplus electricity. Few studies proposed to generate hydrogen by using this surplus electricity through water electrolysis and use it as an alternative storage. Process is formally called “Power to gas” (Akarsu & Serdar Genç, 2022). Table 2.10 shows a summary of literature review that proposed this option.

Table 2.10: Decentralized HESs with hydrogen as the storage option

Authors (year)	Location of study	Energy combinations	Objective	Outcome
Ruilian Wang & Zhang, (2023)	China	Wind-electrolyser-hydrogen tank-fuel cell	To minimize annualize cost and COE	From 0-20% LPSP, COE varies $0.697/kWh-$0.377/kWh
Ma & Yuan, (2023)	China	Solar-Battery-hydrogen storage system	To compare economic factors for solar-battery and solar-hydrogen storage system	Study showed that the combination of solar-battery was economic for rural areas
Al-Buraiki & Al-Sharafi, (2022)	Dhahran, Saudi Arabia	Solar-wind-battery-hydrogen tank-electrolyser	To study the hydrogen loss probability and hydrogen production cost	Study showed that the COE-$0.593/kWh and cost of hydrogen -$36.32/kg for the combination of solar-wind-battery-hydrogen storage
Greiml et al., (2021)	Austria	Solar-hydrogen-synthetic natural gas (SNG)	To perform techno-economic assessment of renewable-based hydrogen and SNG production	Study reported that the cost for hydrogen and SNG were €Cent 11.7-14/kWh and €Cent14-16.4/kWh respectively
Nasiraghdam & Safari, (2020)	Iran	Distributed energy resources-energy storage system-hydrogen storage	To evaluate the techno-economic feasibility of hydrogen storage system	Study showed that the hydrogen storage system reduced the operational cost by 40%
Yinglong Wang et al., (2019)	China	Comparison of coal to hydrogen and biomass to hydrogen production system	To analyse exergy efficiency	Exergy efficiency of coal to hydrogen was 0.15% higher as compared to the biomass to hydrogen system
Rahil et al., (2018)	Libya	Renewable-based off-grid system-electrolyser-hydrogen tank	To analyse hydrogen fuel production cost used for transport	Study reported that the long-term fluctuation was 35% higher as compared to the short-term fluctuation
Mukherjee et al., (2017)	Canada	Solar-wind-hydrogen tank-	To evaluate economic	Study showed that the

		fuel cell-electrolyser	feasibility of different combinations	combination of solar-wind-fuel cell had $41.2M system cost with hydrogen cost was $8/kg
Olateju et al., (2016)	Alberta, Canada	Wind-electrolyser-energy storage	To evaluate hydrogen production cost through different wind farms	Study reported that if the existing wind system was used it reduced the hydrogen production cost by 62.5%

2.11 Desalination and decentralized HESs:

To produce cost-effective potable water from the sea water through desalination required energy for the process may be generate from locally available renewable energy resources (Baleta et al., 2019). Summary of previous literature that analysed this topic is discussed in Table 2.11.

Table 2.11: Desalination and decentralized HESs

Authors (year)	**Location of study**	**Objective**	**Outcome**
Najafi & Talebi, (2023)	Turkey	To evaluate the techno-environmental aspects of the multi-effect desalination (MED)- reverse osmosis (RO) hybrid system coupled with NuScale small modular reactor system	Study showed that the system releases 244,000-ton CO2 in the environment and reduce the environmental impact
Usman et al., (2021)	Canada	To study the techno-economic feasibility of solar thermal based membrane desalination (MD) technique	Study showed that the cost of water from renewable based MD was reduced by 76% from the grid power MD system
Elmaadawy et al., (2020)	Abo Ramad, Egypt	To find the techno-economic with emission from hybrid system for powering RO system	Study showed that the combination of solar-wind-DG-battery system outperformed other combinations
Padrón et al., (2019)	Morocco	To assess the techno-economic feasibility of	Study reported that the combination of solar-wind-DG system

		renewable-based RO system	supplied power to RO system at a COE-$0.404/kWh
Gökçek, (2018)	Bozcaada island, Turkey	To evaluate the economic feasibility of renewable-based RO system	Study reported that solar-wind-DG based RO system reduced the water cost to $2.20/m^3
Christ et al., (2017)	Western Australia	To evaluate the economic feasibility of geothermal energy-based RO system	Study showed that the system reduces the water cost to A$1.56-2.52/m^3
Mentis et al., (2016)	Greece	To evaluate renewable-based RO system for three islands	Study showed that the water cost was reduced by 62-79% from the existing cost
Guillén-Burrieza et al., (2015)	Spain	To evaluate economic feasibility of solar-based RO system	The result showed that the water cost was more for the solar driven RO with respect to the fossil fuel-based systems

2.12 Concluding remarks from the literature review:

The following conclusive remarks emerges from the extensive literature review that is discussed in previous sections:

- Most of the studies used MCDM methods to find the weights and the ranking of the alternatives without considering linguistic uncertainties. Few limited analyses used FMCDM to improve the outcome of the analysis. However, determination of weights and alternatives ranking are much more complicated and uncertain. No significant studies were done to properly prioritize the energy strategies by considering high linguistic uncertainties associated with weights of the criteria and ranking of the alternatives.
- Previous studies mostly analysed suitable location selection either for solar or wind farms without considering detailed linguistic uncertainties. Suitable site selection for decentralized HESs with more complexities and linguistic uncertainties of the weights of criteria were rarely studied in previous literature.
- Studies mostly focused on developed countries. Very few recent studies were focused on villages of India. However, no significant studies were found that performed techno-

economic optimization to obtain optimal decentralized HESs for villages, specifically at remote locations of India.

- Most of the studies performed environmental impact assessment due to emission only for the components. Detailed environmental impact including other impacts by LCA of decentralized HES rarely found in literature.

- Assessment of risk in ROI for decentralized HESs was not significantly analysed in reported literature.

- Most of the previous studies performed techno-economic optimization for decentralized HESs integrated with LA or Li-ion batteries. Few recent studies considered other storage systems like VRF or Ni-CD. However, other electro-chemical storage systems such as ZB and mechanical storage systems like pumped hydro systems are now in use. No previous analysis significantly performed techno-economic comparison of decentralized HESs integrated with these storage systems.

- Previous studies proposed to generate hydrogen from surplus electricity and use it as a storage. The studies mostly performed techno-economic assessment of these systems. Techno-economic optimization with financial risk assessment for such new emerging technologies along with the comparison of this systems with other conventional storage modules say LA and Li-ion were not reported in previous analysis.

- Previous literature only performed techno-economic optimization for renewable resource-based RO desalination for rural villages. Comparison of three mostly used desalination units, viz., MSF, MED, and RO integrated with decentralized HESs for rural villages of India, were not reported significantly in previous analysis.

2.13 Objective of this work

Based on the identified research gaps from the comprehensive literature review, following objectives are decided to explore in this work:

➢ Implementation of HES has several issues. A comprehensive SWOT-MCDM analysis is required to identify these issues and their priorities. A methodology by integrating both SWOT and more improved Hesitant Fuzzy MCDM methods that are explored to determine the strategies and decide the priorities of implementing these strategies for decentralized renewable HESs for Indian villages by considering linguistic uncertainties.

➢ Renewable resources are mostly location dependent. Selection of the most suitable location out of available options for successful implementation of a HES is critical. A methodology that integrates GIS with improved and efficient hesitant fuzzy linguistic MCDM

(HFL-MCDM) to find suitable locations for developing decentralized HES at remote villages of India is developed.

- Supplying steady grid power to high mountains is mostly difficult. Techno-economically optimum decentralized HES is explored for the remote rural villages of north-eastern hilly region of India, i.e., for the difficult Himalayan terrains of India.
- Combined environmental impact assessment through LCA of decentralized HESs along with the techno-economic optimization is done to explore better sustainable energy solutions for rural India, specifically for remote locations.
- There is always a risk in ROI for new technologies. For successful implementation of such technologies scientific assessment of this risk is critical for the investors. Methodology to assess uncertainties in ROI for such systems is also studied.
- With intermittency in renewable resources and variability of load, storage systems are an integral part of decentralized renewable HES. However, the performance of storage systems depends on several operating parameters and these are to be optimized. To improve the techno-economic performance of decentralized HESs integrated with storage systems, different electrochemical energy storage systems and mechanical storage systems integrated with HES are compared under different dispatch strategies.
- Hydrogen is the cleanest fuel and India has currently given special importance to the future hydrogen economy. Producing hydrogen from renewable resources, called green hydrogen, is the best option in this regard. Excess electricity from HES may be used for producing green hydrogen as a storage option. Comparison between green hydrogen with other conventional storage systems in terms of techno-economic performance factors and risk in ROI is studied.
- India has a long coast line and simultaneously severe ground water crisis. Desalination is emerging as a critical need of India. Integrating decentralized renewable HESs with desalination may be a critical need for rural energy and water solutions for a sustainable society. Techno-economic feasibility of different desalination units powered by decentralized HESs are also explored.

2.14. Importance of the thesis:

This thesis is motivated towards deciding overall sustainable decentralized hybrid energy systems with varying resources and needs, specifically for India. To fulfil this objective, studies are carried out for different locations of India with widely varying topography. The resources vary widely for these study locations and local needs are also different. Accordingly the integrated energy systems based on inputs and outputs vary also widely. However, each recommended solution is different though the overall objective of determining the optimum sustainable solution is the same. The developed integrated methodology is thus generic yet novel and the results may vary for different locations.

Chapter-3

Strengths, weaknesses, opportunities and threats determination and prioritization of Indian energy strategies*

(***Das, S.**, De, S.* (2023): Strengths, weaknesses, opportunities and threats determination and strategy prioritization using hesitant fuzzy decision-making approach for better energy sustainability: demonstration with Indian data. **Energy Conversion and Management (Elsevier) (Published). DOI:** https://doi.org/10.1016/j.enconman.2023.116847)

3.1 Objective of the work:

The study is aimed to decide the right priority of energy strategies emerging out of conflicting issues for an extensive planning of actions. The proposed method considered the linguistic uncertainties for the process of determining both weights and rankings. Hence this proposed methodology is more efficient to estimate the priorities of the energy strategy to follow the sustainable development path. For effective planning of actions, the proposed methodology integrates the SWOT method with MCDM, i.e., the HFL-MCDM. Considering the complex, ambiguous and uncertain nature of energy strategy prioritization the HFL-MCDM approach is used to estimate the weights and ranks of the strategies. HFL-Analytic Hierarchy Process (AHP) is used to estimate the weights of the developed strategies. After that, to estimate the rank of these strategies, the HFL-Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method is considered. Additionally, the sensitivity analysis is also performed to evaluate the robustness of the solution.

3.2 Methods:

The proposed methodology simultaneously designs energy strategies by SWOT and decides the priorities using the HFL-MCDM approach for better sustainable energy transition.

3.2.1 India’s energy planning situation:

With the current global trend of energy transition, India also needs to implement new policies and strategies (Government of India, 2016). Though the Indian government announced “Indian vision 2040” for providing reliable, sustainable, efficient and affordable “Power to all” in the country (NITI Aayog, 2017), owing to the above-mentioned problem the energy demand supply gap of the country is significantly increasing (NITI Aayog, 2022b). This is a hindrance to economic development and threatens the future energy security of the country. Developing new energy policies with proper priority is the major challenge to maintain the energy distribution and management for future energy security and to achieve the SDGs of the country (NITI Aayog, 2017). Detailed methodology of this study is shown in Fig. 3.1.

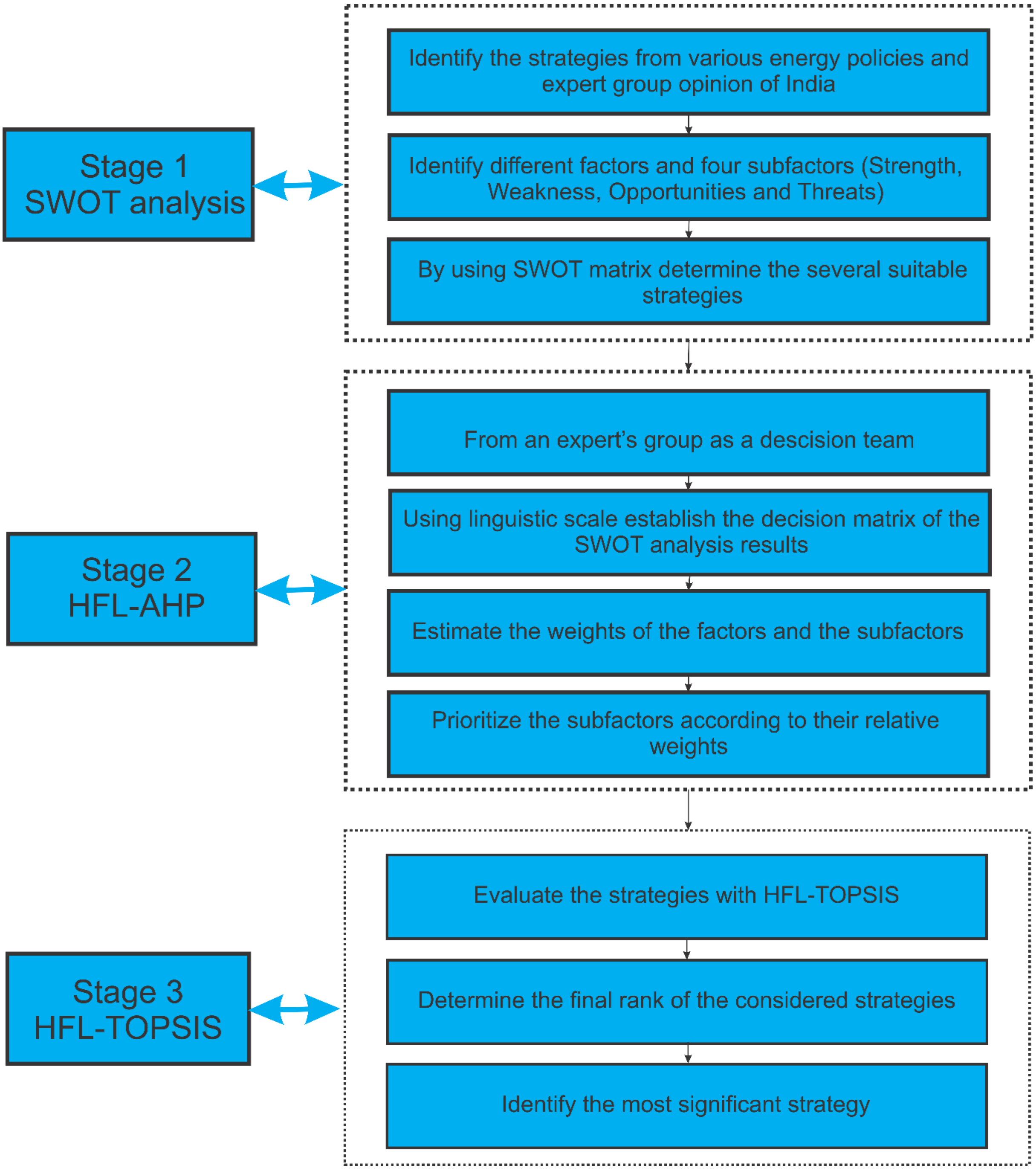


Fig. 3.1: Flowchart of the integrated methodology

According to Fig. 3.1, different tools with the inputs from the previous phase are integrated in this study to decide the priorities of the decided strategies for a better sustainable energy transition.

3.2.2 Strengths, Weaknesses, Opportunities, Threats analysis:

The SWOT analysis is developed by the American businessman and management consultant A.S. Humphrey. This analysis deals with the complex strategy planning, evaluating and organizing these as external and internal factors (Bas, 2013). The two main phases of SWOT analysis are – the SWOT matrix construction, and developing the strategies using this SWOT matrix. The SWOT matrix development involves two major steps: - enlist the factors under strengths (S) and weaknesses (W) which are considered as the internal features and distribute the rest of the constraints under opportunities (O) and threats (T) which are the external features of the SWOT analysis.

The four types of strategies are offered by this SWOT matrix. After determining the S, W, O and T, the matrix is formed by using their combinations, which manifests into four pair of strategies, i.e., strengths-opportunities (SO), strengths-threats (ST), weaknesses- opportunities (WO), and weaknesses- threats (WT) respectively (Alptekin, 2013).The purpose of SO strategies is to determine the optimal use of the internal factor, i.e., strengths and the external factor, i.e., opportunities. The WO strategy is designed to reduce the weaknesses (internal factor) by optimally using the opportunities (external factor). The ST strategies are developed to eliminate the threats (external factor) by using the strengths in the best way. Finally, the WT strategies are formed to minimize the external threats by considering the internal weaknesses.

3.2.3 Hesitant Fuzzy Linguistic Term Set:

The literature showed that several MCDM techniques are used to decide the priority of the developed energy strategies through SWOT analysis to reduce the associated complexities and difficulties. Various MCDM approaches such as AHP, ANP, TOPSIS, ELECTRE III, Preference Ranking Organization Method for Enrichment of Evaluations (PROMETHEE), Weighted Aggregated Sum-Product Assessment (WASPAS), Additive Ratio Assessment (ARAS) are applied in different energy planning problems (Martín-Gamboa et al., 2017). These methods only considered the quantitate values and were unable to overcome the limitation of linguistic uncertainty. The advantages of extended MCDM that includes the linguistic uncertainty to address the issues are discussed in ref. (Yang et al., 2023). According to the literature, this linguistic MCDM methods is able to solve the problem of decision-maker's ambiguity and fuzziness. Considering the uncertainties regarding energy planning problems, a few previous studies used the F-MCDM approaches for deciding the ranking of the energy strategies. The F-MCDM approaches such as F-AHP, F-TOPSIS etc. are gaining interest due to their advantages of solving uncertain decision problems. However, the fuzzy approach is unable to tackle the detailed linguistic terminologies. If the stakeholders are confused among several linguistic terminologies to provide their evaluation, a HFLTS approach is developed to elucidate the expressions of comparative linguistic terms in a hesitant condition. The detailed working principle of the linguistic approach is shown in Fig. 3.2 (Liu & Rodríguez, 2014). This approach makes the linguistic expressions more flexible and generalized by using the context free grammars due to which it becomes nearer to the human cognitive model. Owing to this advantage this approach gives more flexibility to the decision makers so that they can freely express their choice in comparative linguistic terms at hesitant conditions. Among the approaches, HFL-AHP and HFL-TOPSIS are the most recommended MCDM techniques. The advantages of HFL-AHP (Büyüközkan & Güler, 2021) and HFL-TOPSIS (Mi et al., 2019) approaches are discussed in previous references. Considering the advantages of these two techniques the study integrates the techniques with SWOT analysis.

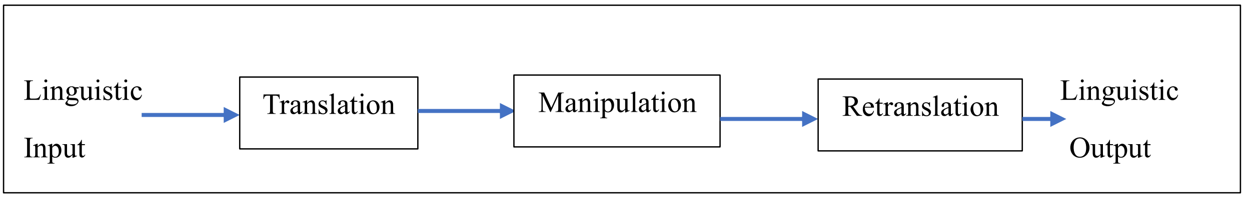


Fig. 3.2: Flowchart of word scheme computation (Liu & Rodríguez, 2014)

Torra first proposed this HFLTS in his study and the degree of membership of an alternative may have several possible values between 0-1 (Torra, 2010). During the assessment the HFLTS approach is useful to solve the hesitant expressions and therefore it is very popular to the researchers to deal with high level uncertainty problems. The studies done by Liu and Rodriguez showed that an MCDM approach with linguistic expressions is appropriate to assess decision-making problems (Liu & Rodríguez, 2014).

The methodology of this HFLTS is discussed below (Torra, 2010):

$$P = \{< y, h_p(P) > | y \in Y\} \quad (3.1)$$

Where P is subset within the range of [0, 1], Y is the set, $h_p(y)$ is the function.

The set of membership function n is written as $M = \{\mu_1, \mu_2, \ldots, \mu_n\}$. The function $h_p(y)$ is related with M and it is defined as (Vicenc Torra, 2010)

$$h_M = M \to \{|0, 1|\} \quad (3.2)$$

$$h_M(y) = \cup_{\mu \in M}\{\mu(y)\} \quad (3.3)$$

$S = \{s_o, \ldots, s_g\}$ is the set of linguistic terms and H_s is the subset of S.

The function that transforms expressions in words under HFLTS, H_s is P_{Gh}. G_h is the grammar used in the linguistic term set (LTS) S, S_{ll} is the domain of the expressions generated by G_h. The relationship is represented by Eq. 3.4 (Torra, 2010).

$$P_{Gh}: S_{ll} \rightarrow H_s \tag{3.4}$$

The following approaches convert the comparative linguistic expression in HFLTS (Torra, 2010):

$$P_{Gh}(s_i) = \{s_i | s_i \in S\} \tag{3.5}$$

$$P_{Gh}(at\ most\ s_i) = \{s_j | s_j \in S\ et\ s_j \leq s_i\} \tag{3.6}$$

$$P_{Gh}(lesser\ than\ s_i) = \{s_j | s_j \in S\ et\ s_j < s_i\} \tag{3.7}$$

$$P_{Gh}(at\ least\ s_i) = \{s_j | s_j \in S\ et\ s_j \geq s_i\} \tag{3.8}$$

$$P_{Gh}(greater\ than\ s_i) = \{s_j | s_j \in S\ et\ s_j > s_i\} \tag{3.9}$$

$$P_{Gh}\left(between\ s_i\ and\ s_j\right) = \{s_k | s_k \in S\ and\ s_i \leq s_k \leq s_j\} \tag{3.10}$$

env (H_s) is defined as the HFLTS envelope and it is the linguistic interval within upper and lower boundaries of H_{s+} and H_{s-}, respectively. It is shown in Eq. 3.11 (Torra, 2010).

$$env(H_s) = [H_{s-}, H_{s+}], H_{s-} \leq H_{s+} \tag{3.11}$$

The two major advantages of this linguistic expression that brings a model environment are- the model provides the large set of the expressions that reduce the hesitance of the experts, and it is also helpful due to the organic adaption of the expressions conserving their unique nature (Mi et al., 2019). In this study, HFL-AHP and HFL-TOPSIS methods are used for estimating the weight and the ranking of the factors and the subfactors respectively. The working principle of these techniques is described in Fig. 3.3.

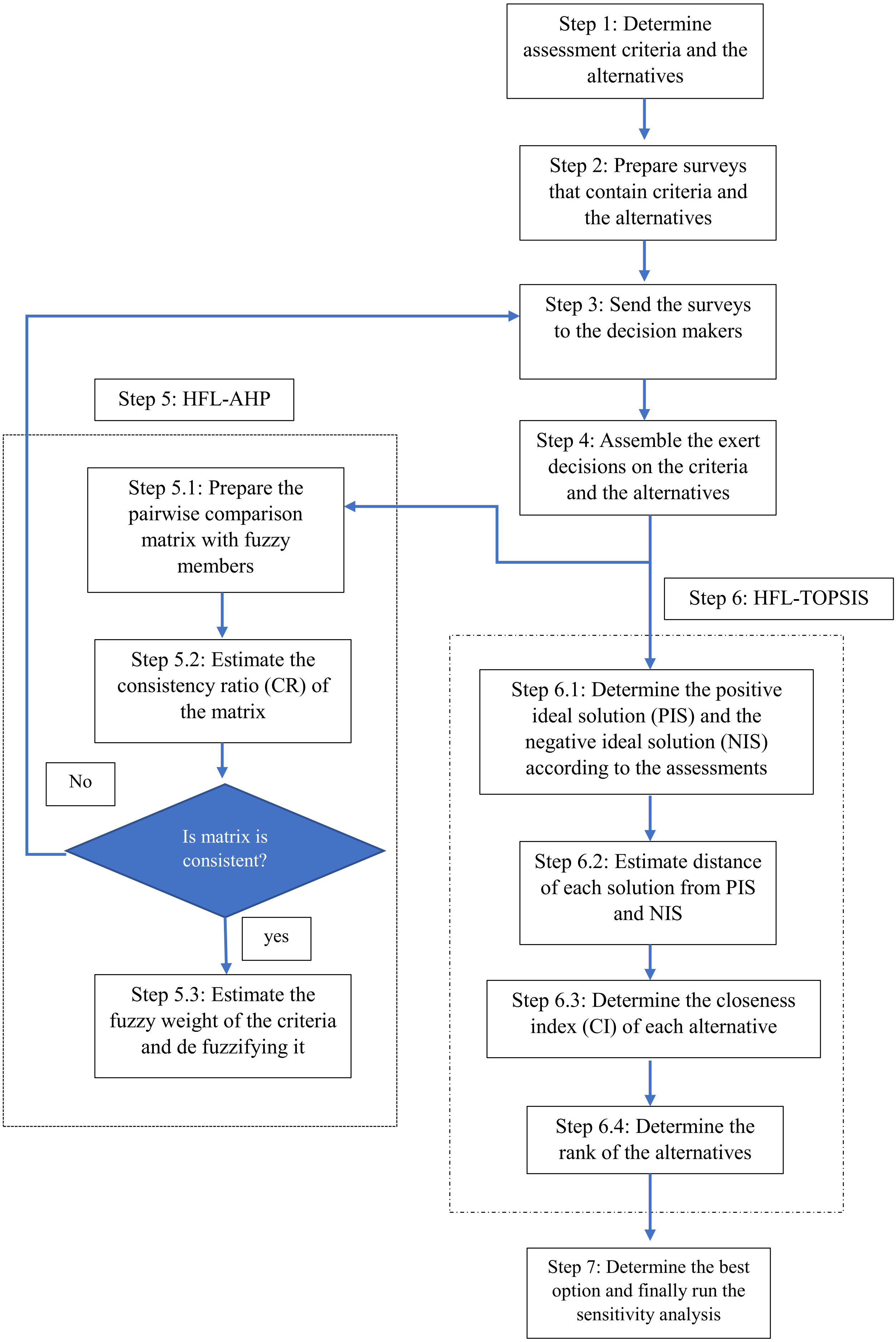


Fig. 3.3: Working principle of HFL-AHP and HFL-TOPSIS methods

3.2.3.1 Hesitant fuzzy linguistic term set-AHP:

The HFL-AHP method is introduced by Saaty which is a strong and simple decision-making approach (Saaty, 1988). It is widely used in calculating the weights of the factors. Figure 3.4 shows the steps followed in this approach to calculate the weights of the factors (Ervural et al., 2018). The scale related to the linguistic terms is shown in Table 3.1 (Ervural et al., 2018).

Table 3.1: Linguistic term scale of the HFL-AHP (Ervural et al., 2018)

Linguistic Term	S_i	Abb.	TFN
Definitely high importance	s10	DHI	(7,9,9)
Extremely high importance	s9	EXHI	(5,7,9)
Essentially high importance	s8	ESHI	(3,5,7)
Weakly high importance	s7	WHI	(1,3,5)
Equally high importance	s6	EHI	(1,1,3)
Exactly low importance	s5	EE	(1,1,1)
Equally low importance	s4	ELI	(0.33,1,1)
Weakly low importance	s3	WLI	(0.2, 0.33,1)
Essentially low importance	s2	ESLI	(0.14,0.2,0.33)
Extremely low importance	s1	EXLI	(0.11,0.14,0.2)
Definitely low importance	s0	DLI	(0.11,0.11,0.14)

The weight factor is calculated in AHP by using Eq. 3.12 (Büyüközkan et al., 2021):

$$F(a_1, a_2, \ldots\ldots, a_n) = wb^T = \sum_{i=1}^{n} w_i b_i \quad (3.12)$$

Where F is the ordered weighted average (OWA) operator w is the weighting vector and it is represented as $(w_1, w_2, \ldots, w_n)^T$ and it belongs to 0-1 with $\sum_{i=1}^{n} w_i = 1$, b is the ordered value vector for the same weighting vector and b_i belongs to b is the largest i^{th} value in A. A is the set of values needed to aggregate and it is $(a_1, a_2, \ldots, a_n)$.

The consistency of the matrix is calculated by using Eq. 3.13 (Adem et al., 2018).

$$\mu_d = \frac{l + m_1 + m_2 + u}{6} \quad (3.13)$$

Where $A = (l, m_1, m_2, u)$ is the triangular fuzzy number (TFN)

Consistency ratio (CR) and consistency Index (CI) are calculated using Eqs. 3.14 and 3.15 (Büyüközkan et al., 2021). The CR measures the degree of departure from pure inconsistency.

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (3.14)$$

Where n is the total criteria number and λ_{max} is the highest eigenvector value of the matrix.

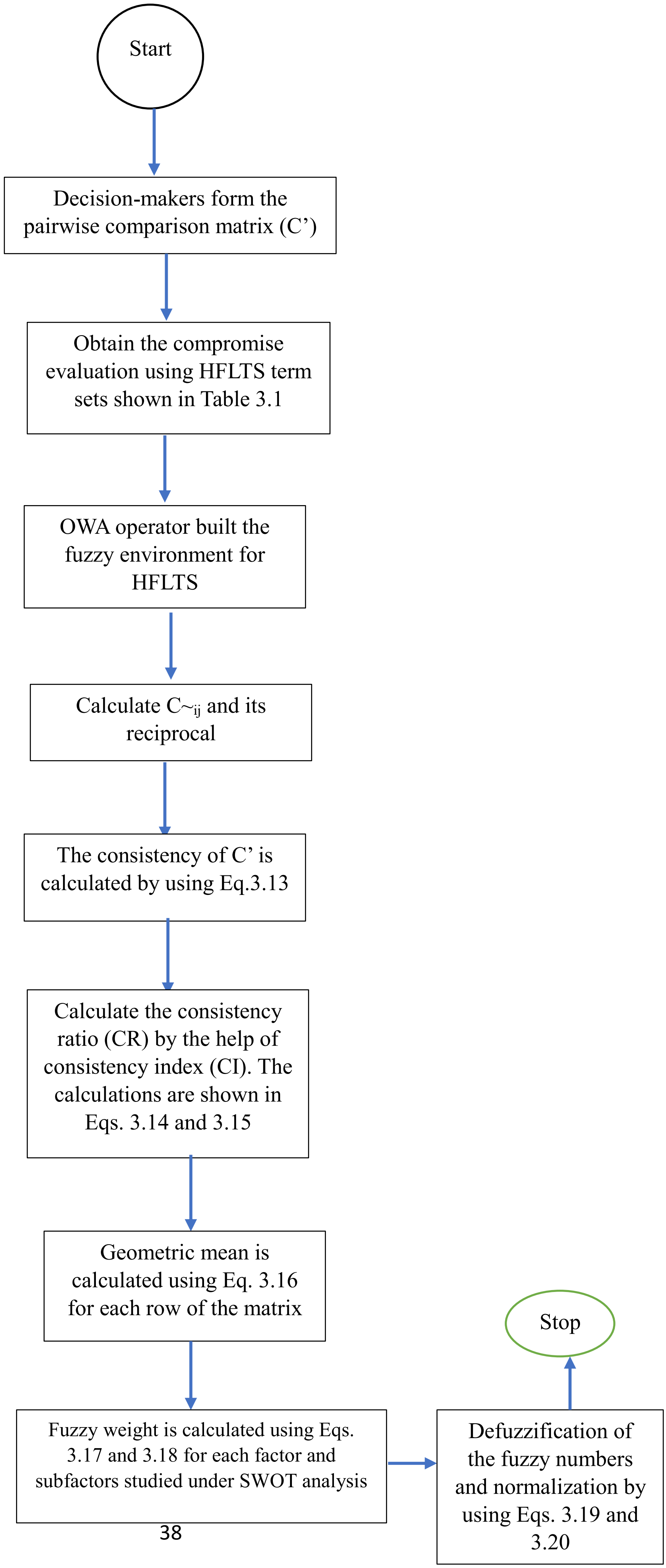


Fig. 3.4: Steps of HFL-AHP for calculating the weights of the factors (Saaty, 1988)

$$CR = \frac{CI}{RI} \tag{3.15}$$

Where RI is the random index.

Fuzzy geometric mean (GM) is estimated using Eq. 3.16 (Büyüközkan et al., 2021).

$$r_i^{\sim} = (c\sim_{i1} \otimes c\sim_{i2} \otimes \quad \ldots . \otimes c\sim_{in})^{\frac{1}{n}} \tag{3.16}$$

Where $\check{r}_i$ is the row number and $\check{c}_i$ is the matrix.

Fuzzy weight $\breve{w}_i^{CR}$ is estimated using Eqs. 3.17 and 3.18 (Büyüközkan et al., 2021). Fuzzy weights are the relative weights for each alternative under a considered criteria. It represent the weight of each criterion with respect to the total objective. To obtain the overall performance of each alternative a weighted sum value (WSV) is obtained.

$$\breve{w}_i^{CR} = r_i^{\sim} \otimes (\tilde{r}_1 \otimes \tilde{r}_2 \otimes \ldots . \otimes \tilde{r}_n) \tag{3.17}$$

$$\widetilde{w}_{ij}^{G} = \breve{w}_i^{CR} \times \breve{w}_j^{CR} \tag{3.18}$$

Where $\hat{w}^{G}_{ij}$ is the weight of the subfactors and $\check{r}_i$ is the row number. $\hat{w}^{G}_{ij}$ and $\hat{w}^{N}_{ij}$ are calculated using Eqs. 3.19 and 3.20 respectively (Büyüközkan et al., 2021).

$$w_{ij}^{G} = \frac{\alpha + 2\beta + 2\gamma + \delta}{6} \tag{3.19}$$

$$w_{ij}^{N} = \frac{w_{ij}^{G}}{\sum_i \sum_j w_{ij}^{G}} \tag{3.20}$$

3.2.3.2 Hesitant fuzzy linguistic-TOPSIS:

Hwang and Yoon proposed this MCDM approach which assesses the alternatives according to their distances from the ideal solution (Çolak & Kaya, 2017). The HFL-TOPSIS approach firstly determines the fuzzy evaluation matrix which then constructs the evaluation matrix. Then sequentially fuzzy decision matrices, fuzzy normalized matrix, and weighted normalized matrix are developed with regard to each strategy. Then the positive ideal solution (PIS) and negative ideal solution (NIS) are estimated depending on the criteria. Then the distances of each alternative from PIS and NIS are estimated (Çolak & Kaya, 2017). Using these values, the relative closeness index (RI) value is calculated. In the final stage, the highest RI value is considered as the best solution. In this study, the HFL-TOPSIS approach is used to deal with the uncertainties in decision making problems. The steps of this HFL-TOPSIS method is discussed below (Çolak & Kaya, 2017):

Step 1: The PIS and NIS are estimated using Eqs 3.21 and 3.22 (Çolak & Kaya, 2017)

$$A^* = \{h_1^*, h_2^*, \dots, h_n^*\} \quad (3.21)$$

$$A^- = \{h_1^-, h_2^-, \dots, h_n^-\} \quad (3.22)$$

Where

$$h_j^* = \cup_{i=1}^{m} h_{ij} = \cup_{\gamma 1j \in h_{1j}, \dots, \gamma mj \in h_{mj}}, \max\{\gamma_{1j}, \dots, \gamma_{mj}\} \; j = 1,2, \dots, n \quad (3.23)$$

$$h_j^- = \cap_{i=1}^{m} h_{ij} = \cap_{\gamma 1j \in h_{1j}, \dots, \gamma mj \in h_{mj}}, \max\{\gamma_{1j}, \dots, \gamma_{mj}\} \; j = 1,2, \dots, n \quad (3.24)$$

Step 2: Each alternative's distance from PIS and NIS is estimated using Eqs. 3.25 and 3.26 (Çolak & Kaya, 2017). In this analysis, weighted hesitant normalized Euclidean distance method is used for the calculation.

$$D_i^+ = \sum_{j=1}^{n} w_j ||h_{ij} - h_j^*|| \quad (3.25)$$

$$D_i^- = \sum_{j=1}^{n} w_j ||h_{ij} - h_j^-|| \quad (3.26)$$

Where w_j is the crisp weight of the jth criteria.

Step 3: The RI is calculated using Eq. 3.27 which helps to rank the alternatives (Çolak & Kaya, 2017):

$$C_i = \frac{D_i^-}{D_i^- + D_i^+} \quad (3.27)$$

Step 4: The alternatives are ranked by using the RI value. The alternative with the highest RI value has been considered as the best option.

3.2.4 Application of proposed methodology with India's energy sector data:

The proposed integrated methodology is applied to identify the strategies for the national energy sector and set the priorities of those for India. Detailed literature review is done to gain a comprehensive knowledge for determining an appropriate energy strategy planning. These strategies for India are within one of the four factors, i.e., S, W, O, and T according to their characteristics. Then using the SWOT matrix SO, WO, ST, and WT are formed. From SWOT analysis, the factors (both internal and external) influencing sustainable energy transition of India are determined. In this study, 17 subfactors are identified from a reference (Nag & Sarkar, 2018) and Energy Policy of India (NITI Aayog, 2022b). All the relevant factors and the subfactors suitable for sustainable energy planning of the country are described in Fig. 3.5. The developed strategies are shown in Table 3.2. In the next step HFL-MCDM approach is integrated with the SWOT analysis to prioritize the strategies so that these can be more effectively implemented for better energy transition towards sustainability.

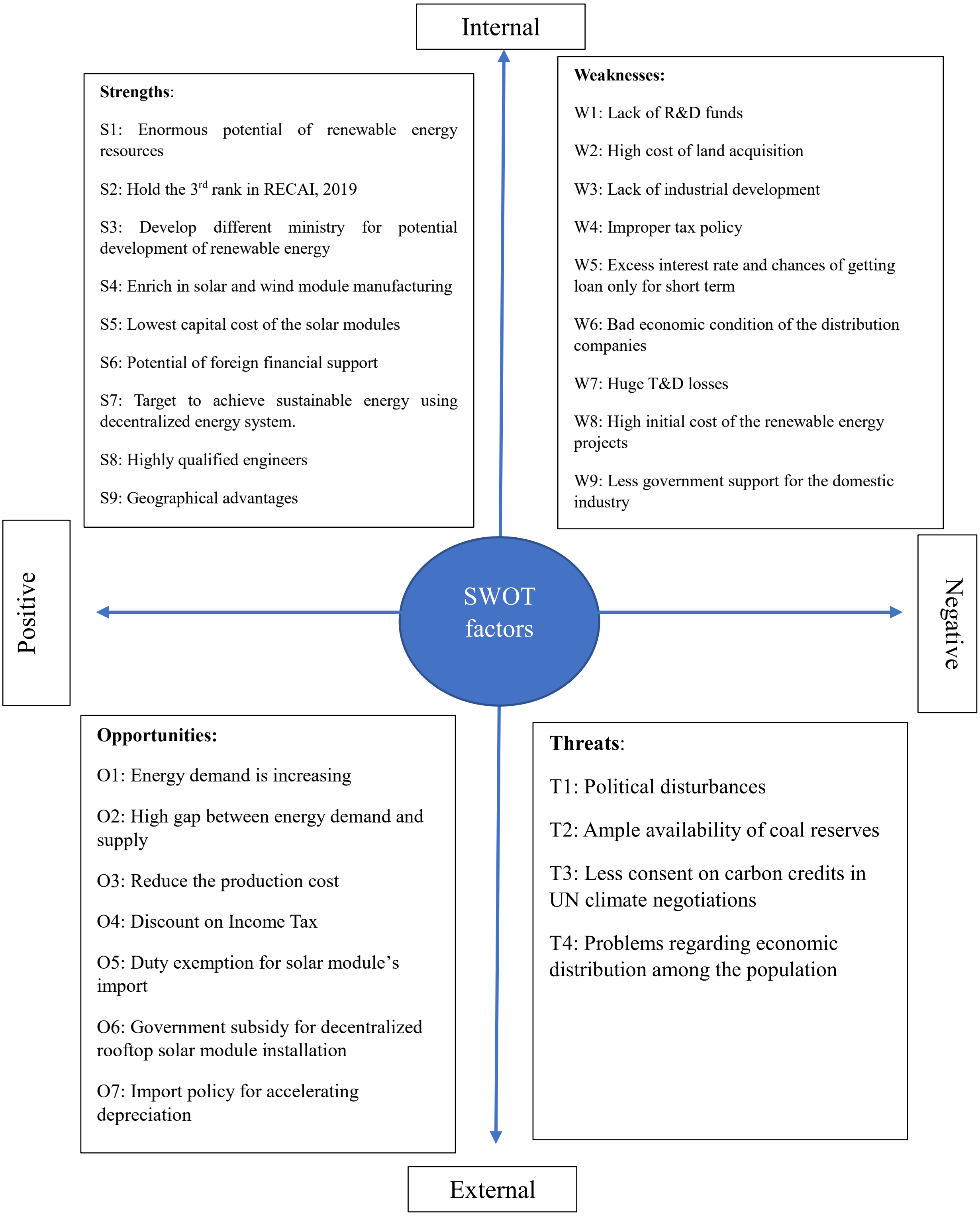


Fig. 3.5: SWOT analysis of India's energy planning system [NITI Aayog, 2022b, Nag & Sarkar, 2018]

The strategies that shown in Table 3.2 are discussed in more detail here:

Table 3.2: SWOT energy planning strategies for the Indian scenario:

	Strengths (S)	**Weaknesses (W)**
	Strength-Opportunities (SO) strategies	**Weakness-Opportunities (WO) strategies**
Opportunities (O)	**SO1**: Increase the renewable energy share in energy mix to reduce the demand supply gap. **SO2**: Improving the technical infrastructure of the energy industry. **SO3**: Increase the regional support to provide the reliable energy supplies. **SO4**: Enhance the foreign supports.	**WO1:** To eliminate the demand supply gap increase the energy efficiency. **WO2**: Improve the energy market environment for future investment. **WO3**: Reliable electricity supply to various sectors at minimum economy **WO4**: Import taxes on CES to harness the usage of fossil-fuel-based energy resources for electricity generation.
	Strength-Threats (ST) strategies	**Weakness-Threats (WT) strategies**
Threats (T)	**ST1**: Increasing the RE penetration to mitigate the environmental challenges **ST2**: Creating diversity in energy resources by giving priority to the locally available options. **ST3**: Using the new views and advertising ways to develop the energy sector. **ST4**: Concentrate on developing decentralized renewable energy solution.	**WT1**: Increase the R&D activities in this energy sector **WT2**: Increase the coordination between the suppliers and the customers and also strengthen the cooperation between public and private sector. **WT3**: Reduces the operational and financial inadequacies of the locality. **WT4**: Decrease the economic losses in the electricity generation system **WT5**: Reduce the local political influences at the time of localized energy generation construction.

The strategies can be further discussed extensively as follows.

3.2.4.1 SO (Strengths-Opportunities) strategies:

SO1 strategy: This strategy is focused on increasing the energy production from renewable energy resources. By increasing the renewable energy share in energy production, it is possible to reduce the energy demand crisis by minimizing the CO_2 emission. The renewable energy resources (especially solar, wind and small hydro) in India are abundantly available, and a proper energy planning may help to tap these resources efficiently (Ramesh & Saini, 2020).

SO2 strategy: The strategy is emphasized on developing the technical infrastructure related to the energy industry for efficient usage of the renewable resources.

SO3 strategy: This strategy is intended to maximize regional cooperation and support, so that it ensures the continuous energy supply.

SO4 strategy: The strategy is focused to ensure the foreign support and investments to expand the energy generation capacity. The government is liable to prioritize the strategies so that it can enhance the usage of renewable energy resources that are abundantly available through foreign and regional support and cooperation.

3.2.4.2 WO (Weaknesses-Opportunities) strategies:

WO1 strategy: This strategy is considered to reduce the energy demand-supply gap by increasing the potential of energy efficiency. By utilizing the energy efficient devices, it is possible to increase the energy conservation efficiency and reduce the transmission and distribution (T&D) losses which are the main deciding factors to improve the energy reliability.

WO2 strategy: The strategy is referred to improve the energy market environment for exploring the opportunities of future investment. The energy sector of the country is suffering due to less investment which is considered in this strategy and to overcome the situation it is recommended to address investment friendly strategies for maintaining the stable energy supply.

WO3 strategy: The strategy is focused to supply reliable and continuous electricity at least cost to various sectors. This strategy ensures the access of sustainable electricity for all sectors of consumers at an affordable cost.

WO4 strategy: This strategy is aimed to reduce the usage of conventional energy sources (CES) by importing high amounts of taxes on it. The implementation of taxes on CES import can reduce the fossil fuel reliance. This demands suitable planning and strategies from policymakers to support indigenous energy development activities.

3.2.4.3 ST (Strengths- Threats) strategies:

ST1 strategy: This strategy is emphasized on increasing the alternative energy penetration to minimize the environmental degradation which reduces the climate change impact.

ST2 strategy: The strategy is aimed to diversify the energy resource option to secure the future energy security. As the resources are intermittent and regional therefore the efforts of this strategy are to consider the locally available renewable resources for stable energy supply.

ST3 strategy: This strategy is focused to bring new ideas and different innovative advertisements in the energy sector to increase the people’s attraction towards renewable energy resource utilization. The strategy is initiated to increase the society's concern over renewable energy resource utilization.

ST4 strategy: This strategy is developed to increase the decentralized hybrid energy systems for supplying reliable and continuous power to the locality at minimum cost. As the renewable energy resources are intermittent and regional as well as it is difficult to extend the centralized grid system to the remote areas therefore the efforts of this strategy are to develop this system for sustainable supply in these areas.

3.2.4.4 WT (Weaknesses- Threats) strategies:

WT1 strategy: This strategy is mainly focused to increase the research and development (R&D) activities in the energy sector for maximizing energy efficiency. This strategy is the pivotal for sustainable energy strategy development and can effectively help to explore the possible renewable energy projects to maintain the future energy security.

WT2 strategy: This strategy emphasizes on improving the coordination between distributor and consumers and also strengthening the bonding of public and private sectors.

WT3 strategy: The strategy is focused to minimize the operational and financial inefficiencies in the electricity supply sector by reducing the T&D losses and improving the overall financial structure.

WT4 strategy: The strategy is referred to restrict the financial losses in the electricity generation sector which occurred due to poor financial structure, mismanagement and corruption. The introduction of this strategy encourages the power management and economy of the sector at par with international standards and practices.

WT5 strategy: This strategy is focused to reduce the local political influence at the time of decentralized energy system development. This reduces the cost of the development, mismanagement and other different problems related to the energy sector.

Therefore, besides policy development, prioritizing them would increase the energy supply reliability and enhance the future energy security.

3.3 Results and discussions:

The integrated framework of SWOT analysis, HFL-AHP and HFL-TOPSIS approach is considered as a methodology of this study. Figure 3.6 shows the steps followed at the time of implementation of this integrated framework on the energy strategy design. The outlines of the framework are a feasible process which helps the policymakers to prioritize the strategies of the country's energy planning in a sustainable way.

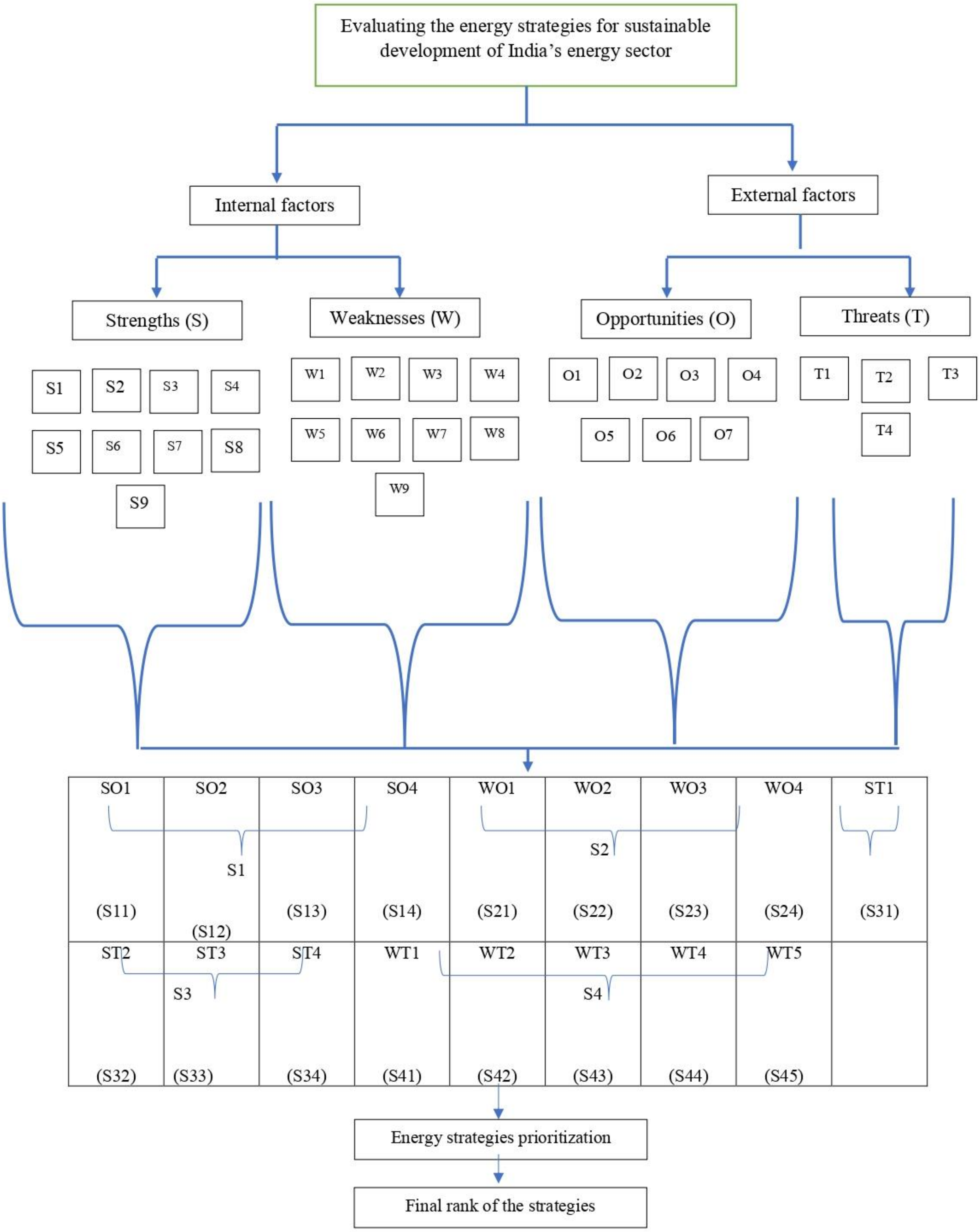


Fig. 3.6: Energy strategy prioritization framework for India's energy planning

According to Fig. 3.6, the identified strategies are classified under four main factors, i.e., S, W, O and T using the SWOT analysis. Strengths and weaknesses are the internal factors and opportunities and threats are the external factors. Then through the SWOT matrix analysis based on combinations of classified strategies subfactors are developed, say, SO, WO, ST and WT. The strategies divided under four factors integrated under these subfactors to strengthen the strategies by using the opportunities and weakening the threats. The SWOT matrix is developed on the basis of the following factors and subfactors which are shown in Table 3.2. To decide the weights and the rankings of these factors and the subfactors the HFL-AHP and HFL-TOPSIS approach are used.

3.3.1 Weights analysis results:

The matrices are related to pairwise comparisons which are formed by using the SWOT analysis factors and subfactors with respect to the decision goals. To calculate the weight of these factors and the subfactors the HFL-AHP method is used. According to the HFL-AHP methodology this weight is obtained using the expert's judgement. To aggregate the individual priorities in group decision making, both the GM and the arithmetic progression (AP) are used. The GM approach is considered in this study as it is the most reliable and robust method with respect to the meaning of the decisions (Solangi et al., 2019). The final priority matrices are then estimated, which provides the decided ranking of SWOT factors and subfactors.

3.3.1.1 Weights of the SWOT factors:

Firstly, to understand the importance of the factors the weights of the SWOT factors are determined and the analysis result is shown in Fig. 3.7.

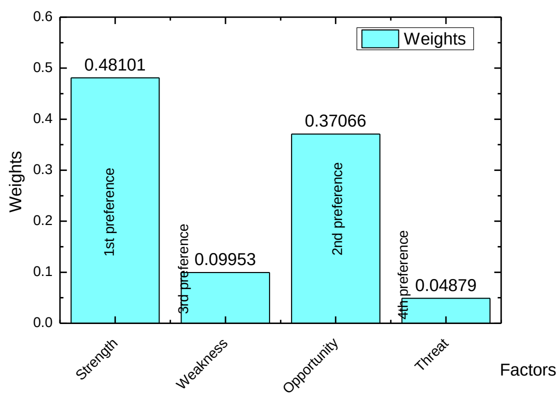


Fig. 3.7: Estimated weights of the SWOT factors

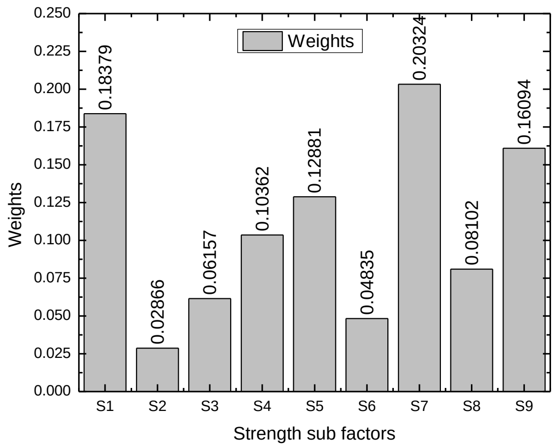
According to Fig. 3.7, S is the most important factor with a weight of 0.481 followed by O (weight- 0.371), W (weight- 0.099) and T (weight- 0.049). The detailed weight calculation process is shown in Table 3.3. This table shows that the CR value is less than 0.1 and according to HFL-AHP if the CR is less than 0.1 then the analysis result is accepted (Büyüközkan et al., 2021). The result shows the importance of considering S factor in the energy planning process of India. In the next step, the weights of the subfactors are estimated.

Table 3.3: Weights and the consistency ratios (CRs) of the factors of the SWOT analysis:

Factors	**WSV**	**λ**	**λ_{max}**	**CI**	**CR**	**CR<0.1**
Strengths	2.061528	4.285795	4.173673123	0.057891041	0.064323379	TRUE (Acceptable)
Weaknesses	0.403879	4.057696				
Opportunities	1.59868	4.313021				
Threats	0.197015	4.038181				

3.3.1.2 Weights of the Strengths subfactors:

The weights of the subfactors of the strength factor are calculated using the HFL-AHP approach and the result is shown in Fig. 3.8. The detailed weight analysis result is shown in Table 3.4.



Fig, 3.8: The weights of the subfactors considered under strength criterion

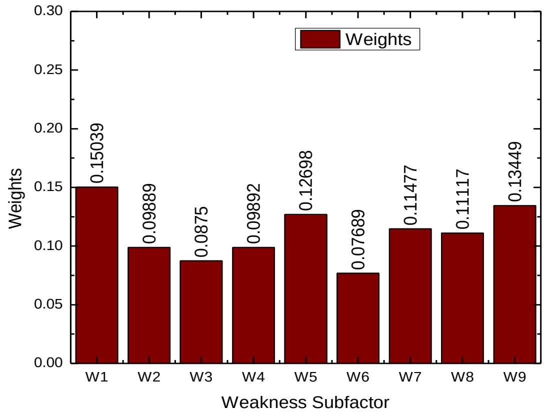
According to the figure, the highest weight (0.203) is obtained for the subfactor S7 – "Target to achieve sustainable energy solution" followed by the subfactors S1, S9, S5, S4, S8, S3, S6, S2. The highest weight of the subfactor S1 is in line with the prediction of the literature that India is shifting towards renewable power. It is the best possible sustainable option. The subfactor S3 "Obtain the 3rd ranking in RECAI, 2019" is the least desired strategy for the country. The priority of the S7 strategy is 10.9% higher as compared to S1 strategy. The weight estimation of the subfactors help to decide the rank of the strategies. The CR value shown in Table 3.4 justifies the acceptance of the analysis.

Table 3.4: Weights of the strength subfactors and CR values:

Subfactors	WSV	λ	Λ_{max}	CI	CR	
S1	1.684774	9.166718	10.0575	0.132188	0.091164	0.091164<0.1 (Acceptable)
S2	0.273676	9.550729				
S3	0.595687	9.675563				
S4	1.083764	10.45908				
S5	1.355999	10.52678				
S6	0.433601	8.96812				
S7	2.2742	11.1896				
S8	0.836243	10.32152				
S9	1.715547	10.65942				

3.3.1.3 Weighs of the Weaknesses subfactors:

The weight of the subfactors of the weakness factor is shown in Fig. 3.9 and the detailed analysis of weight calculation is shown in Table 3.5.



Fig, 3.9: The weights of the subfactors considered under the weakness criterion

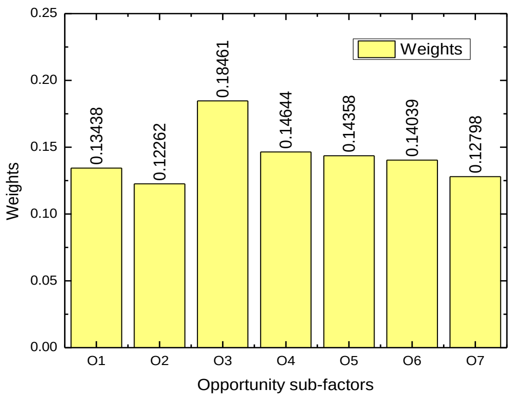
According to this figure, the weight is maximum (0.1504) for the subfactor W1 – "Lack of R&D funds". This finding reveals that expert's apprehension pertaining to the lack of research and development funds in the energy strategy activities in India. This fact is mentioned in the literature that India is spending less in the R&D sector. The second highest weight is obtained for the subfactor W9- "Less government support for the domestic industry". Less governmental support for mitigating energy crises and improving energy security are the key issues that are addressed here. The least weight is obtained for W6- "bad economic condition of the distribution companies". Table shows the CR ratio and the value is 0.082. It signifies that the calculation is acceptable. For sustainable development of the country through establishing the energy security of the country "R&D funds related to the energy sector", "government support", "increase energy system's efficiency" need to get more attention.

Table 3.5: Weights of the weakness subfactors and CR values:

Subfactors	WSV	λ	Λ_{max}	CI	CR	
W1	1.51335	10.06259				
W2	0.998223	10.09461	9.956346	0.119543	0.082444	
W3	0.853796	9.758077				
W4	0.978015	9.886419				
W5	1.277719	10.06253				0.082444<0.1 (Acceptable)
W6	0.768085	9.989398				
W7	1.120228	9.760942				
W8	1.077813	9.694793				
W9	1.384941	10.29776				

3.3.1.4 Weights of the Opportunities subfactors:

The weights of the subfactors considered under the opportunity factor are shown in Fig. 3.10. The CR value of the analysis is 0.092 which is shown in Table 3.6. The highest weight (0.185) is obtained for the subfactor O3– “Reduce the production cost” followed by O4, O5, O6, O1, O7, O2. It is a very significant strategy that seeks to reduce the electricity production cost in India. The discount on Income tax is the next highest weight subfactor. This prioritization encourages to increase the diversity in energy mix for electricity generation from conventional resources to renewable resources. To adopt renewable energy technologies, the Government should implement new financial mechanisms, increase environmental awareness and promote the benefits of these technologies. The prioritization of “duty exemption for solar module’s import” maximizes the renewable energy share. The weight distribution reflects reduced awareness of this energy strategy.



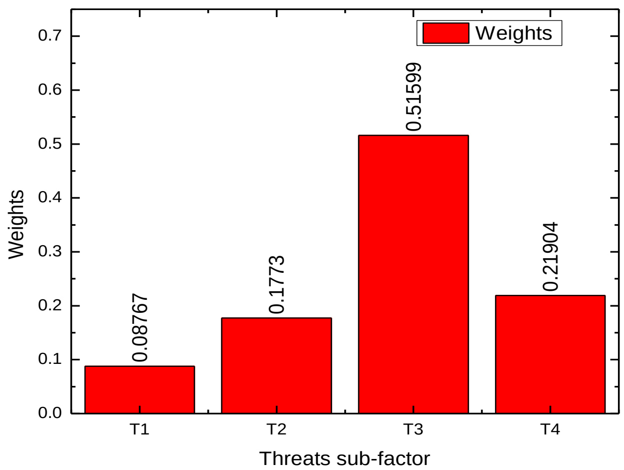
Fig, 3.10: The weights of the subfactors considered under the opportunity criterion

Table 3.6: Weights of the opportunity subfactors and CR values:

	WSV	λ	Λ_{max}	CI	CR	
O1	1.035676	7.707171	7.730293	0.121716	0.092209	0.092209<0.1 (Acceptable)
O2	0.92678	7.558019				
O3	1.418352	7.683123				
O4	1.108624	7.570457				
O5	1.102845	7.680801				
O6	1.128786	8.040421				
O7	1.007459	7.872059				

3.3.1.5 Weights of the Threats subfactors:

The estimated weights of the subfactors considered under the threat factor is shown in Fig. 3.11. Table 3.7 shows the CR analysis result of the HFL-AHP approach. According to the figure, the maximum weight is obtained for the subfactor T3 which is 0.516. The second highest subfactor is T4 with the weight of 0.22 followed by T2 (0.177) and T1 (0.088). According to the analysis, the maximum priority is given to the subfactor T3 which emphasized on "Less consent on carbon credits in UN climate negotiations". Minimizing the threats according to the priority shown in Fig. 3.11, it can reduce the weaknesses of the country's energy sector and strengthen the energy strategy for sustainable energy planning.



Fig, 3.11: The weights of the subfactors considered under the threat criterion

Table 3.7: Weights of the threat subfactors and CR values:

	WSV	λ	Λ_{max}	CI	CR	
T1	0.35949	4.100448	4.132542	0.044181	0.049089	0.049089<0.1 (Acceptable)
T2	0.721829	4.071266				

T3	2.14337	4.15393
T4	0.920979	4.204522

3.3.1.6 Weights of the overall subfactors:

In this analysis, a total of 29 subfactors are analysed and their weights are estimated after examining their internal correlations. The result is shown in Fig. 3.12. According to the analysis, among the overall subfactors S7 subfactor is of the maximum weight (approximately 0.05911). The S7 subfactor is in line with the country's sustainable development goal policy. The CR value is less than 0.1 as shown in Table 3.8.

It is observed from the analysis that attaining sustainable energy solution (S7), taking the geographical advantages for local resource utilization (S9), economic distribution problems among the population (T4) and enormous renewable energy potential (S1) are the key subfactors for sustainable energy planning for India.

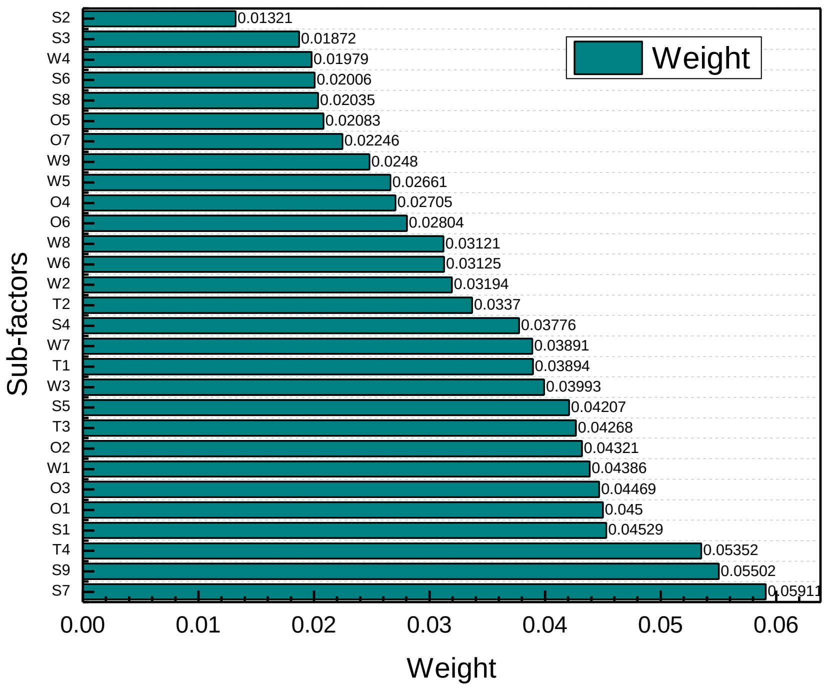


Fig. 3.12: Weights and rankings of overall subfactors of SWOT analysis

Table 3.8: Weights of overall subfactors and the CR values:

	Criteria weight	Weighted sum value	(WSV/CW)	Λ_{max}	CI	CR	CR<0.1
S1	0.045288	1.53063	33.79773	33.80766	0.171702	0.099827	TRUE
S2	0.013206	0.449279	34.02052				
S3	0.018719	0.62647	33.4664				
S4	0.037762	1.258677	33.33203				
S5	0.042072	1.430404	33.9987				
S6	0.020056	0.674634	33.63742				
S7	0.059109	2.019821	34.17125				
S8	0.020347	0.67261	33.05767				
S9	0.055024	1.858134	33.76954				
W1	0.043863	1.484896	33.85321				
W2	0.031939	1.082124	33.88082				
W3	0.039926	1.362051	34.11416				
W4	0.019792	0.669226	33.81314				
W5	0.026605	0.902338	33.91611				
W6	0.031254	1.052973	33.69074				
W7	0.038907	1.326852	34.10307				
W8	0.031208	1.053898	33.76965				
W9	0.024798	0.83633	33.72535				
O1	0.045003	1.531002	34.01965				
O2	0.043205	1.458391	33.75509				
O3	0.044689	1.529174	34.21818				
O4	0.027055	0.941886	34.81395				
O5	0.020829	0.698865	33.55311				
O6	0.028043	0.93925	33.49323				
O7	0.022461	0.748367	33.31871				
T1	0.038943	1.306434	33.54702				
T2	0.033698	1.131603	33.58108				
T3	0.042678	1.459506	34.19845				
T4	0.053521	1.80934	33.80625				

3.3.2 Energy prioritization analysis result:

After calculating the weights of the factors and the subfactors the HFL-TOPSIS method is used to decide the rank of the developed strategies which is designed through the SWOT analysis method. The ranking of the 17 energy planning strategies is shown in Table 3.9. Figure 3.13 shows the closeness coefficient value along with the rank of the strategies. The strategies are briefly discussed according to their rank to justify the calculated priority order as follows:

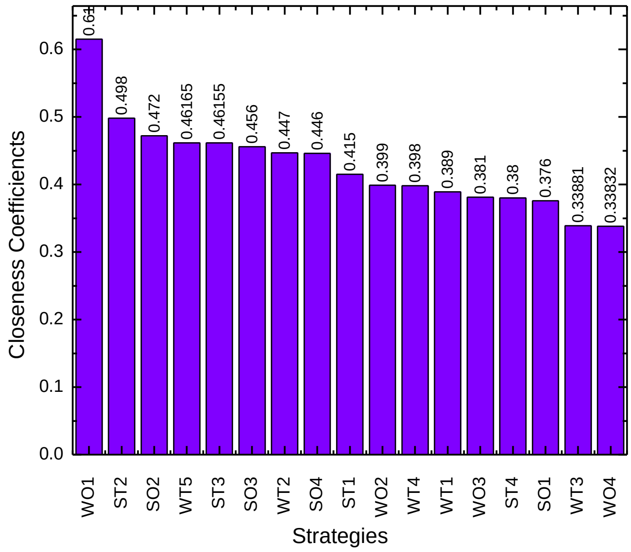


Fig. 3.13: Ranking of the strategies

Table 3.9: Rank of the considered strategies:

Strategies	Distance to the FPIS (d_i^*)	Distance to the FNIS (d_i^-)	Closeness coefficient (CC_i)	Rank
S01	98.475059	59.841024	0.377984493	15
SO2	84.880212	76.090915	0.47269915	3
SO3	85.68094	71.746344	0.455742755	6
SO4	89.532053	72.095033	0.446057864	8
WO1	60.172452	96.477785	0.615880238	1
WO2	98.25516	65.702071	0.40072689	10
WO3	96.903596	60.104774	0.382812546	13
WO4	106.64988	54.531057	0.338322003	17
ST1	89.185824	63.311678	0.415165346	9
ST2	80.06656	79.656422	0.498716097	2
ST3	84.130929	72.114388	0.461545917	5
ST4	95.975301	59.402391	0.382309648	14
WT1	94.938618	60.756221	0.390226301	12
WT2	86.846751	70.258789	0.447207585	7
WT3	103.22111	52.892594	0.338808142	16
WT4	94.791667	63.092927	0.399614208	11
WT5	86.057177	73.525911	0.461649804	5

3.3.2.1 WO1 strategy (Rank 1):

The strategy is decided to eliminate the demand supply gap by increasing the efficiency. By improving the efficiency of the energy system, the competitiveness of the component increases. This helps to minimize the energy security risk as well as the environmental challenges confronted by the country. The maximum amount of energy is consumed by the residential and the transport sectors. Therefore, energy efficiency maximization is the significant endeavour for sustainable energy planning (Guterres, 2020).

3.3.2.2 ST2 strategy (Rank 2):

Renewable energy in India is abundantly available. Though the country has potential indigenous CES, experts are recommending to exploit the available clean energy resources on a high priority. By integrating these CES along with the RE in an appropriate and effective way it can minimize the energy demand crisis of the country.

3.3.2.3 SO2 strategy (Rank 3):

The technical inefficiency causes T&D losses. Due to which the chance of power failure increases. Owing to these reliable and continuous power supplies become difficult in the remote locations of the country. Hence, this strategy is recommended to improve the technical infrastructure of the energy system that can increase the efficiency of the system. By increasing the efficiency, the losses of the energy systems are reduced and it is possible to provide stable, continuous and reliable supply in the remote regions of the country.

3.3.2.4 WT5 strategy (Rank 4):

This strategy is recommended because India is the largest democratic country in the world. Therefore, several political conflicts arise at the time of decentralized energy system construction. This affects the development of the country. Therefore, this strategy needs to be a high priority. By taking proper steps the political conflicts can be minimized which helps to solve several problems at the time of installing new energy systems. This is beneficial for social development.

3.3.2.5 ST3 strategy (Rank 5):

The people from the remote areas of the country are still unaware about using clean energy sources. To meet their daily energy requirement, they depend on the local conventional energy resources. Their negligence towards energy resource utilization is hampering the society's development. Hence, the key to the development is creating awareness regarding this issue. Therefore, to achieve the goal this strategy is considered as one of the high priority strategies for the country.

3.3.2.6 SO3 strategy (Rank 6):

It is difficult and expensive to extend the centralized grid system in the remote areas of the country. Hence, to supply reliable and continuous power, decentralized renewable energy system development is the recommended option. As the renewable energy resources are regionalized therefore to construct the decentralized energy resource system the regional support is mandatory. Therefore, this strategy is important and the estimated ranking is justified.

3.3.2.7 WT2 strategy (Rank 7):

For sustainable energy supply and to secure the energy resources for future it is essential to use the resources in an efficient manner. It is important to know the energy demand of the area. Before establishing the new energy system, if the distributors know the proper energy demand of the area, then only it is possible to develop the optimum capacity energy system. Through this it is possible to restrict the cost of electricity (COE). Therefore, the coordination between the distributor and the consumer needs to increase. Also, in the country many private sectors in this field are developing. As the country is still economically poor therefore to provide energy to these remote areas the COE must be economic. Hence, the public and private sectors need to cooperate with each other for supplying reliable and continuous power at an affordable cost. This condition is the main requirement in SDG and thus, this strategy is getting medium priority.

3.3.2.8 SO4 strategy (Rank 8):

The energy sectors are still going through the continuous development process for sustainable energy supply. This continuous development is possible through extensive research. Therefore, to carry out this expenditure of research funding is appropriate. Therefore, foreign financial support is recommended to maintain the extensive research. The estimated priority of this strategy is justified.

3.3.2.9 ST1 strategy (Rank 9):

The availability of the CES in India is limited. As the population of the country is exponentially increasing the energy demand also increases. The energy sector of the country is still dependent on fossil fuels. The fossil fuels are limited and the depletion rate is high. If the consumption of this fuel increases, then in the near future it will culminate. Then the country will face a severe energy crisis. To overcome this situation, it is recommended to follow this strategy. To enhance the energy security for the future by simultaneously reducing the fossil fuel dependency this strategy is emphasized. Considering the need, the estimated priority of this strategy is justified.

3.3.2.10 WO2 strategy (Rank 10):

The continuous development requires high investments. The process of investment distribution and also the corruption of the energy market need to be minimized. The appropriate distribution of the investment enhances the development and increases the research on the energy field. Therefore, this strategy is moderately important.

3.3.2.11 WT4 strategy (Rank 11):

A large number of people in this country are still under the poverty line. To avail the energy the COE must need to be affordable. By minimizing the energy losses at the time of generation it is possible to supply the energy at an affordable cost to the people of the rural and remote areas. Hence, the decided strategy is discreetly significant.

3.3.2.12 WT1 strategy (Rank 12):

The strategy is emphasized to increase the research and development in this energy sector. The extensive research is able to increase the technical efficiency of the system. It helps to reduce the COE and the losses. Therefore, to obtain the sustainable, reliable, continuous energy at minimum economy this strategy needs to apply properly.

3.3.2.13 WO3 strategy (Rank 13):

This strategy is in line with the “Power to all” government mission. According to the policy, the government is bound to supply the electricity to every household at an affordable cost. According to the SDG announced by the UN this is the major concern. Therefore, the policy is temperately substantial for the country's development. Depending on the situation of the country the considered strategy is of moderate priority.

3.3.2.14 ST4 strategy (Rank 14):

The renewable energy resources are intermittent and regionalized. To overcome this challenge developing a decentralized hybrid renewable energy system for the specific locality is the only solution. Hybridizing two or more energy generators and using the locally available renewable resources for a decentralized energy system may solve the intermittency and regional issues. Instead of extending a centralized grid system this option is appropriate for sustainable power supply. As this type of energy system is new for the country it demands extensive research. Therefore, the developed strategy is dependent on several other factors. Due to this reason, the priority of this strategy is still not high.

3.3.2.15 SO1 strategy (Rank 15):

The renewable energy resources are substantially available in India. This strategy emphasized on maximizing the renewable energy share to mitigate the energy demand crisis and CO_2 emission. This strategy is in line with the "India 2040" vision. According to this vision, the government is bound to increase the RE share in a significant amount so that the country can achieve sustainable development goals. The strategy is dependent on other constraints. So, the estimated priority of the strategy is justified.

3.3.2.16 WT3 strategy (Rank 16):

By reducing the financial and operational inadequacies it is possible to supply electricity at an affordable cost to the remote and rural areas of the country. This strategy is important for the country. However, to achieve this strategy several other challenges need to be overcome which is mentioned in the previous strategies. Hence the decided rank of the strategy is appropriate.

3.3.2.17 WO4 strategy (Rank 17):

Approximately 75% of the Indian energy is catered through fossil fuels. India has the potential coal reserve and the country imports crude oil and a few other fossil fuels from other countries. By introducing the taxes, the COE will increase and therefore it is possible to reduce the usage of the sources for energy generation. This strategy is getting the least priority because the implementation process of this strategy is complex and it is also less effective.

After estimating the priority of the developed strategies in this study the sensitivity analysis is performed to evaluate the robustness of the estimated ranking.

3.3.3 Sensitivity study:

To perform this analysis, the weights of the strategies are varied. The response of the ranking for different weights helps to understand the estimated rankings' reliability. This analysis also shows the impact of the subfactors' weights on the ranking of the developed strategies. To pursue the analysis, 10 different cases are constructed and evaluated by varying the weights of the factors to measure the priority of the alternatives. The variable weights for different subfactors are shown in Table 3.10. The analysis result is shown in Table 3.11. From the analysis result it is observable that in the maximum cases, the ranking of the strategies remained the same. The ranking order of a few alternatives such as SO4, WO2, ST1, WT3, and WT4 have changed under the case-4, case-5, case-6 and case-8 respectively. For the rest of the cases, the rankings of the alternatives remain the same with the actual order.

The study results also show that the highest and the least priority strategies (WO1 and WO4) remain unchanged for all the cases. Hence, the sensitivity analysis confirms that the decided priorities are not affected also with limited uncertainties and hence the analysis is robust too.

Table 3.10: Weights of SWOT factors with actual and different other possible cases:

	Actual weight	**Case 1**	**Case 2**	**Case 3**	**Case 4**	**Case 5**	**Case 6**	**Case 7**	**Case 8**	**Case 9**	**Case 10**
Strengths	0.481	0.25	0.30	0.40	0.35	0.20	0.10	0.15	0.30	0.40	0.35
Weaknesses	0.09953	0.25	0.20	0.10	0.15	0.20	0.10	0.15	0.30	0.40	0.35
Opportunities	0.371	0.25	0.30	0.40	0.35	0.30	0.40	0.35	0.20	0.10	0.15
Threats	0.04858	0.25	0.20	0.10	0.15	0.30	0.40	0.35	0.20	0.10	0.15

Table 3.11: Sensitivity analysis result

Strategies	**Actual weight rank**	**Case 1**	**Case 2**	**Case 3**	**Case 4**	**Case 5**	**Case 6**	**Case 7**	**Case 8**	**Case 9**	**Case 10**
SO1	15	15	15	15	15	15	15	15	15	15	15
SO2	3	3	3	3	3	3	3	33	3	3	3
SO3	6	6	6	6	6	6	6	6	6	6	6
SO4	8	8	8	8	10	10	9	8	10	8	8
WO1	1	1	1	1	1	1	1	1	1	1	1
WO2	10	10	10	10	8	8	10	10	8	10	10
WO3	13	13	13	13	13	13	13	13	13	13	13
WO4	17	17	17	17	17	17	17	17	17	17	17
ST1	9	9	9	9	9	9	8	9	9	9	9
ST2	2	2	2	2	2	2	2	2	2	2	2

ST3	5	5	5	5	5	5	5	5	5	5	5
ST4	14	14	14	14	14	14	14	14	14	14	14
WT1	12	12	12	12	12	12	12	12	12	12	12
WT2	7	7	7	7	7	7	7	7	7	7	7
WT3	16	16	16	16	16	16	11	16	11	16	16
WT4	11	11	11	11	11	11	16	11	16	11	11
WT5	4	4	4	4	4	4	4	4	4	4	4

3.4 Summary of the chapter:

Policies have to be adopted with proper priority of strategies based on resources and constraints of a country. The study integrates SWOT-HFL-AHP-HFL-TOPSIS methods to determine and prioritize strategies for successful energy transition of a country. The study developed 17 energy strategies and prioritized those strategies using this methodology. The analysis results show that the WO1 is of the highest priority. This priority is to supply continuous reliable energy for all the sectors of the country. Also, creating diversity in energy resources and using locally available resources to develop energy systems are necessary for reliable energy supply (ST2) is obtained as the next priority. On the other hand, reducing the fossil-fuel based energy system by imposing the taxes on CES (WO4 strategy) is of the least priority. The sensitivity analysis also confirms this result as reliable and robust. The methodology of determining strategies and prioritizing those strategies may provide the energy security of a country.

Chapter-4

Suitable location selection for developing decentralized HESs*

(***Das, S**, De, S, De, S.* (2023): GIS based hesitant fuzzy linguistic-MCDM for optimal locations of decentralized hybrid energy systems. **Energy (Elsevier) (Under Review)**)

4.1 Objective of the work:

The study proposes a methodology integrating GIS with a new accurate fuzzy linguistic term set (FLTS)-MCDM, i.e., New Easy Approach to Fuzzy PROMETHEE (NEAT-F-PROMETHEE). Out of different conflicting issues, it decides the 'optimum' location. Subsequently the sensitivity analysis is carried out to evaluate the robustness and consistency of this solution. The hesitant fuzzy linguistic term set (HFLTS)-MCDM methods are considered for this analysis. In this study, hesitant fuzzy linguistics (HFL)-AHP and HFL-Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) are used to estimate the criteria weights and the ranking of the available alternatives respectively. The methodology will identify the acceptable optimum site location for new installations of HESs with overall best performance.

4.2 Methodology:

This geospatial decision-making analysis methodology is performed in five steps (Phase I-V) shown in Fig. 4.1.

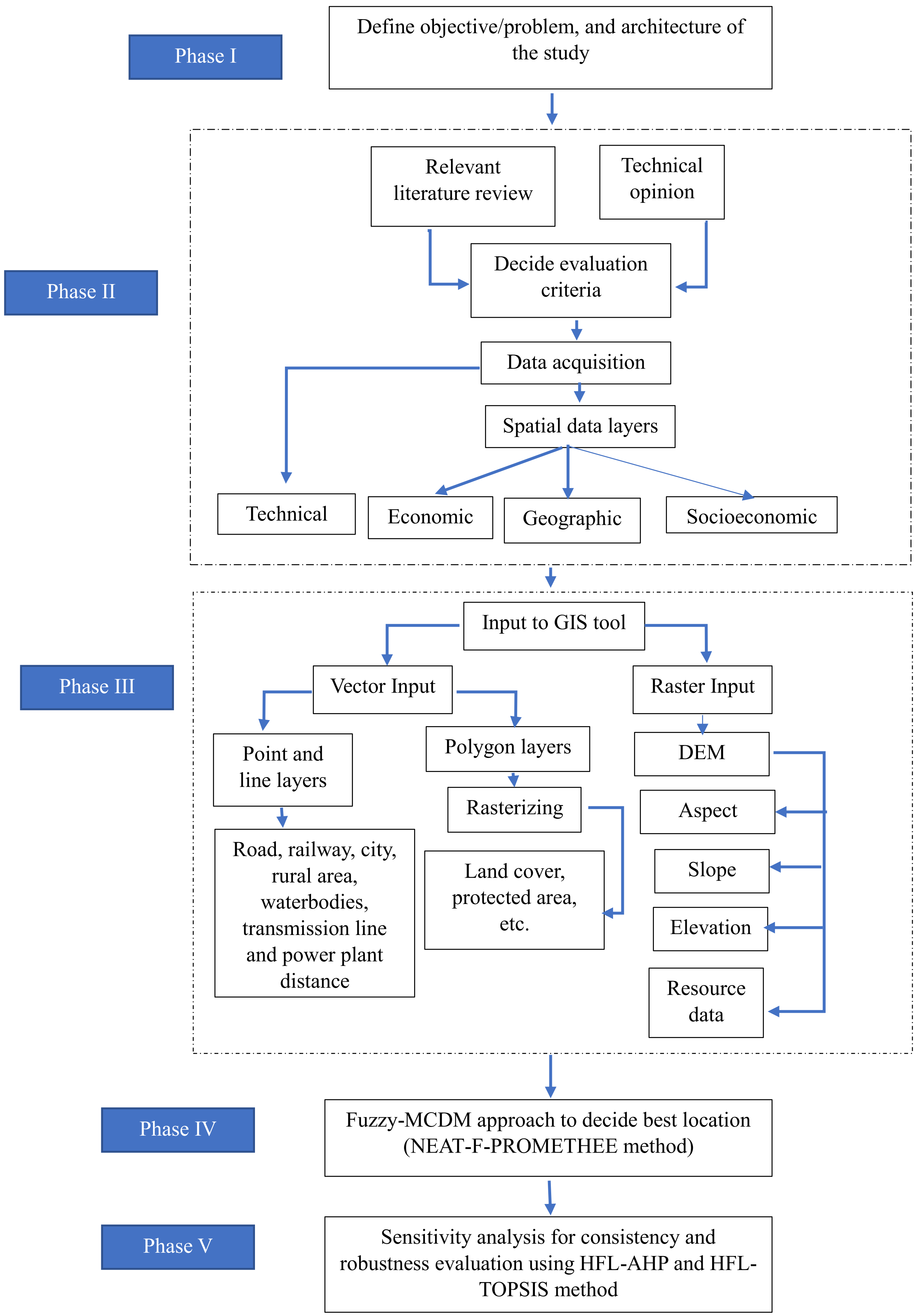


Fig. 4.1: Methodology flowchart

According to Fig. 4.1, the methodology integrates different tools with inputs from the earlier phase towards the goal of deciding acceptable optimum location for a new decentralized HES.

4.2.1 Study area:

The proposed methodology is demonstrated with Indian data. Madhya Pradesh, a central state of India is considered as a study area (Hijmans, 2004). The latitude and longitude of the location are 23.47ºN and 78.66ºE respectively (C. B. of India, 2021). Figure 4.2.a shows the location in the map. Figure 4.2.b shows the different areas in location (Hijmans, 2004). Many remote areas of this state are unable to access reliable and affordable electricity (The Times of India, 2023). Though the state is enriched with solar and wind resources (Central Electricity Authority (Government of India & Power), 2021) several factors are needed to consider to find the suitable location for developing decentralized HESs (The Times of India, 2022). The location details are discussed in Table 4.1 (Government of India, 2021a).

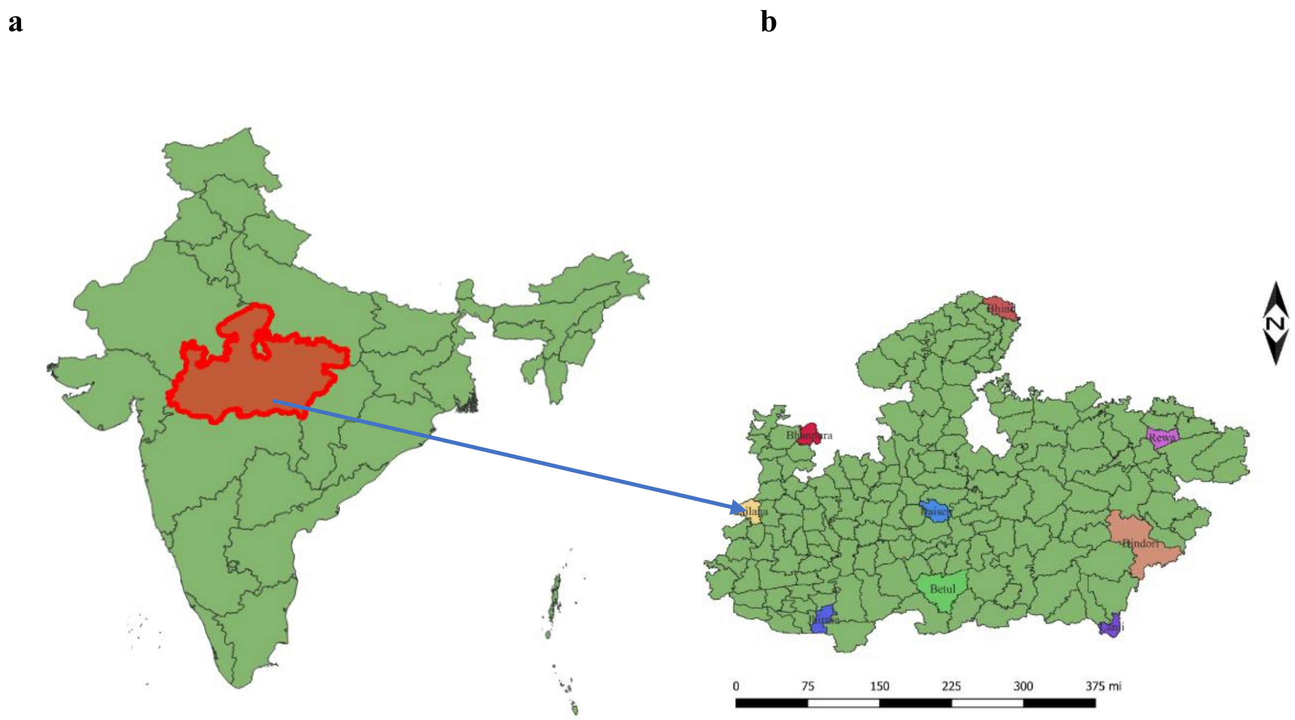


Fig. 4.2.a : Location of the state in Indian Map, b. study areas (Hijmans, 2004)

Table 4.1: The details of alternatives (Government of India, 2021a)

Alternatives	Location	Region	Area (sq. km)	Population
A1	Bhind	Northern region	4459	17,03,005
A2	Bhanpura	North-west Region	3427	7,57,847
A3	Sailana	Western region	8758	1379131

A4	Jhirnia	South-western region	567	7416
A5	Betul	Southern region	10,043	15,75,343
A6	Lanji	South-eastern region	764	13,558
A7	Dindori	Eastern region	7,407	7,04,524
A8	Rewa	North-eastern region	6,314	23,65,106
A9	Raisen	Middle	8,466	13,31,597

4.2.2 Data sources:

This study considered nineteen geospatial data layers mentioned in Table 4.2. Geospatial and attribute data used in this study are obtained from the secondary sources. Data sources for different criteria used to identify and evaluate potential sites to develop solar photovoltaic (PV)-wind based hybrid energy systems in Madhya Pradesh, India. These spatial layers are used as inputs into the GIS for future spatial analysis and sustainability assessment. Solar radiation data and temperature are collected from the global solar atlas, energydata.info (Energydata.info, 2023a). These data are jointly developed by the Ministry of New and Renewable Energy (MNRE), India, the World Bank and the International Finance Corporation. Wind speed of these locations at an altitude of about 100 m above the sea level for a resolution of 1000 m X 1000 m is collected from DTU wind energy Global Wind Atlas, energydata.info (Energydata.info, 2023b). These data are in the form of wind speed frequency distribution for twelve direction sectors. Elevation of ground, slope, aspect, hill shade are generated using global digital elevation model (DEM) and United States Geological Survey (USGS) (United States Geological Survey, 2023) at 30 m resolution and the QGIS spatial analyst toolbox. Roads, railway connection, inland water, population and land use and land cover data are generated from the Digital chart of the world (DIVA-GIS) (Hijmans, 2004) and GIS tool. Urban and rural agglomeration data are obtained from NASA-SEDAC (Earthdata, 2023). Protected area collected from Data Basin, Conservation Biology Institute (2003) (Conservation Biology Institute, 2003). Electric power transmission lines and Power Plants of Madhya Pradesh are obtained from the Power and gas grid map of south Asia (2006) (George et al., 2018), USAID (USAID, 2023), and CARMA power plant dataset (Ummel, 2013) respectively. These data are either in raster format and vector format with a definite resolution mentioned in Table 4.2.

Table 4.2: Used geospatial and thematic layers for site selection of decentralized HES:

No.	Subject	Description	Type	Geometry	Spatial Resolution	References
1	Solar radiation	Global solar irradiance (GHI)-(kWh/m^2/day)	Raster		1000 m	Energydata.info, (2023a)
		Solar Normal radiation (DNI)-(kWh/m^2/day)	Raster		1000 m	
		Diffuse horizontal radiation (DIF) - (kWh/m^2/day)	Raster		1000 m	
		Temperature (ºC)	Raster		1000 m	
		Orientation	Text			
2	Wind speed	Wind speed at a height of 100 m above sea level	Raster		1000 m	Energydata.info, (2023b)
3	Terrain Data	Digital elevation model (DEM) (m)	Raster		30 m	United States Geological Survey, (2023
		Slope (%)	Raster		30 m	
		Aspect (deg)	Raster		30 m	
		Hill shade (m)	Raster		30 m	
4	Roads	Different state and national highway	Shape file	Poly line		Hijmans, (2004)
5	Rails	Rail connections	Shape file	Poly line		
6	Land use	Land use and land covered by forests, wetlands, water bodies, buildings etc.	Raster		50 m	
7	Water bodies	Contains rivers, canals and lakes	Shape file	Polygon and polyline		
8	Rural settlements	Rural area covered in this state	Shape file	Point		Earthdata, (2023)
9	Urban settlements	Urban area covered in this state	Shape file	Point		
10	Protected area	It covers the natural parks, biological corridors, nature reserves etc.	Vector	Polygon	Varied and compiled from different sources	Conservation Biology Institute, (2003)
12	Electricity Infrastructure	Transmission line	Shape file	Poly line		Ummel, 2013; George et al., (2018); USAID, (2023)
		Power plants	Shape file	Point		

4.2.3 Evaluation Criteria:

Based on the defined goal, study area, accessibility of data sets, spatial scale and operational techniques different evaluation criteria are developed. These evaluation criteria are considered on the basis of rigorous literature review. All the possible criteria are considered in this analysis. These criteria are distributed in five main categories, namely resource factors, climatic factors, topographic factors, economic factors, social factors etc. The categories and the sub-categories are shown in Fig. 4.3. The details are discussed in Table 4.3. The beneficial and the non-beneficial distribution of the evaluation criteria are distributed in Table 4.4 (Gao et al., 2022).

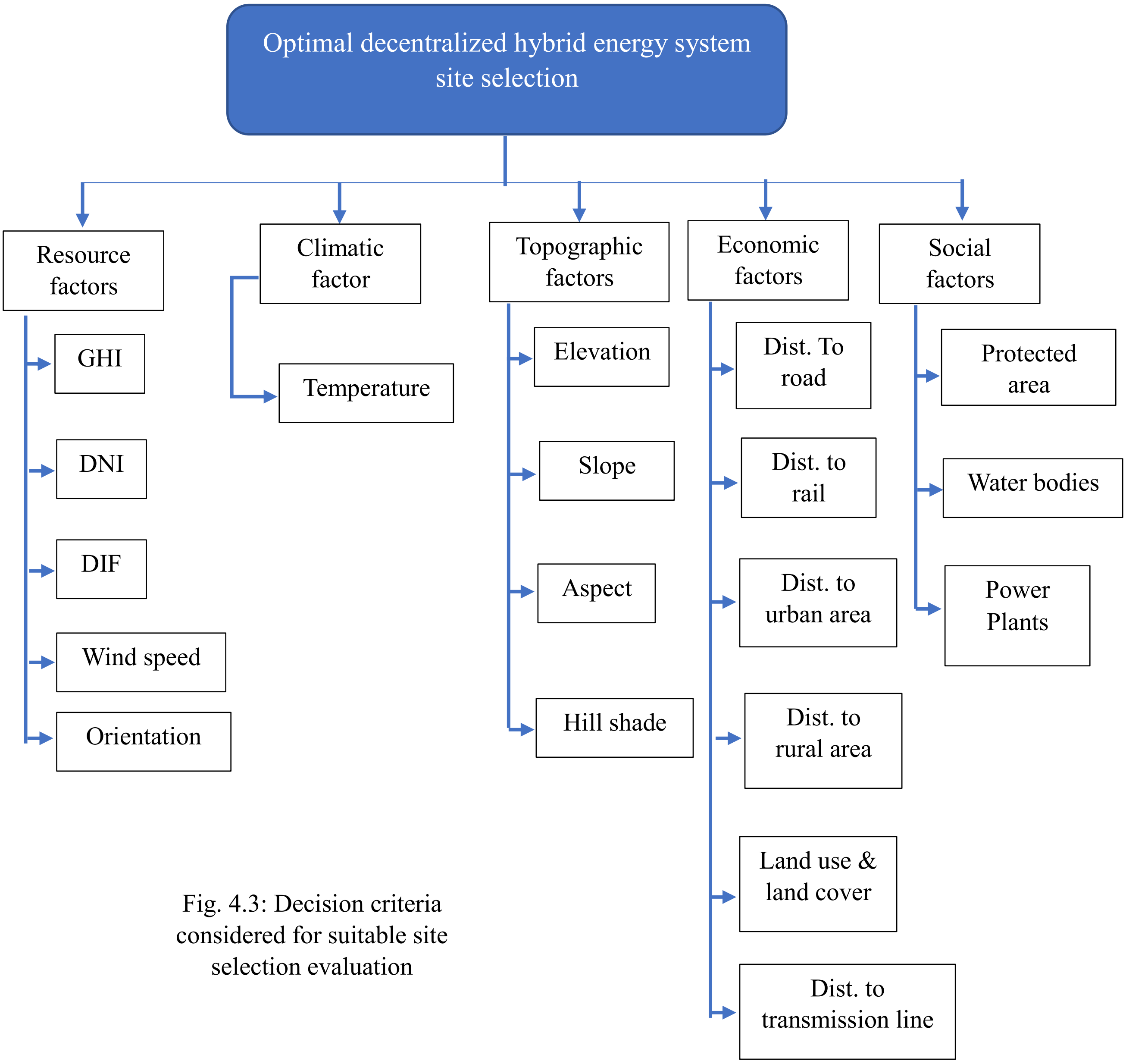


Fig. 4.3: Decision criteria considered for suitable site selection evaluation

Table 4.3: Details of the evaluation criteria

Resource factors	GHI: Helps to determine the potential viability of solar farm development. The total amount of solar radiation that reaches the horizontal surface is

	known as GHI. More amount of GHI is suitable for more PV power energy systems. In solar wind hybrid energy system solar irradiance, wind speed, temperature is considered as the main criteria (Günen, 2021).
	DNI: It is the normal radiation which represents the amount of light coming perpendicular to the surface. Solar panels maximize this by means of tilting or rotating with angle of sun (Günen, 2021).
	DIF: It is the diffused horizontal irradiation which does not arrive at direct path from the sun, but it has been scattered by clouds and particles and comes equally from all direction (Günen, 2021).
	Wind Speed: In terms of techno-economic feasibility to construct the wind farms it is an essential and decisive factor (Barzehkar et al., 2021).
	Orientation: It maximizes the power production from the solar panel. Tilting according to the direction improves the power quality (Saraswat et al., 2021).
Climatic Factor	Temperature: is essential for developing solar farms. High temperature reduces the output power from the panel (Gao et al., 2022).
Topographic factors	Elevation: Both solar irradiance and wind speed are directly related with the elevation. At a higher elevation the performance of solar and wind energy is enhanced (Koc et al., 2019).
	Aspect: the slope of area in which the eight directions face is measured by 0^{o} to 360^{o}. The direction and slope are closely linked and calculation process of both of these is almost similar in major projects. Eight directions are namely North: 0-22.5 and 337.5-360, Northeast: 22.5-67.5, East: 67.5-112.5, Southeast: 112.5-157.5, South: 157.5-202.5, Southwest: 202.5-247.5, West: 247.5-292.5, Northwest: 292.5-337.5, and flat slope is Zero aspect (Günen, 2021; Koc et al., 2019).
	Slope: Steep slopes are majorly unsuitable for developing the project, facilities and power plants. To prepare land, construction installation and maintenance of hybrid energy system is not cost-effective on steep slopes, and maximum 5% slope is suitable for developing the projects (Günen, 2021).
	Hill Shade: Developing projects, facilities and power plants at high hilly areas is not techno-economically feasible (Gao et al., 2022).
Economic factors	Distance to road: Reasonable distance from the highways, main roads is recommended for feasible hybrid energy system development. It reduces the transportation and project costs. The shorter the distance the easier the access and the better the overall feasibility (Günen, 2021).
	Distance to railways: Like main roads and high ways the railway connection also facilitate access to the project site. The proximity to railways is considered as a positive factor (Günen, 2021).
	Distance to urban location: installation of HES nearer to urban areas can harm the urban residents. The expert's advice, technical reports and previous studies suggests that distance >5 km from the urban areas to the project location is suitable for developing these systems (Saraswat et al., 2021).
	Distance to rural settlements: Reasonable distance is essential. If the distance is more, it will increase the transmission cost. Also, less distance can cause harms to the residents of the rural area (Saraswat et al., 2021).
	Land use and Land cover: It is essential yet critical for both the solar and wind farms. It also creates difficulties on construction. Government can take strict policies to install energy systems on agricultural land or pursue more flexible policy. Developing these energy systems at protected areas is usually restricted (Koc et al., 2019).
	Distance from transmission line: Feasible distance of the projects from it is recommended. Depending on the requirement electricity sale and purchase can be possible if the transmission line is at a feasible distance. However, if

	the transmission system is nearer to the project area, then it creates problems to develop these new technologies (Saraswat et al., 2021).
Social factors	Distance to water bodies: To protect water resources, flora and fauna and due to the risk of floods it is recommended to maintain a minimum of 7 km distance from the water bodies (Saraswat et al., 2021).
	Distance to protected area: Developing projects nearer to the protected areas is restricted. Minimum 10 km distance need to be maintained to develop the projects (Gao et al., 2022; Saraswat et al., 2021).
	Distance to power plant: Feasible distance from power plants is essential. It will provide necessary things such as road networks, transmission facilities and water resources. Thus, it will increase the economic viability and environmental stability. According to the expert the land above 10 km from the exiting power plant is suitable for designing this project (Gao et al., 2022; Saraswat et al., 2021).

Table 4.4: Beneficial and non-beneficial distribution of the criteria (Gao et al., 2022)

Criteria	Sub-criteria	Type
Resource factors (C1)	GHI (C11)	Benefit (maximize)
	Wind speed (C12)	Benefit (maximize)
	DNI (C13)	Benefit (maximize)
	DIF (C14)	Benefit (maximize)
	Orientation (C15)	Benefit (maximize)
Climatic factor (C2)	Mean temp (C21)	Non-beneficial (minimize)
Topographic factors (C3)	Elevation (C31)	Benefit (maximize)
	Slope (C32)	Non beneficial (minimize)
	Aspect (C33)	Non beneficial (minimize)
	Hill shade (C34)	Non beneficial (minimize)
Economic factors (C4)	Distance from road (C41)	Non beneficial (minimize)
	Distance from rail (C42)	Non beneficial (minimize)
	Distance from urban settlements (C43)	Non beneficial (minimize)
	Distance from rural settlements (C44)	Non beneficial (minimize)
	Land use (C45)	Non beneficial (minimize)
	Distance from transmission line (C46)	Non beneficial (minimize)
Social factors (C5)	Distance from waterbodies (C51)	Benefit (maximize)
	Distance from protected area (C52)	Benefit (maximize)
	Distance from power plants (C53)	Benefit (maximize)

4.2.4 Veto criteria:

During analysing optimal investment options, any factors that affect the operational performance of decentralized HES projects should be evaluated. To restrict the computation time and decision space, infeasible solutions must be excluded. Table 4.5 shows the limits on the installation of decentralized PV-wind HESs (Aghaloo et al., 2023; Gao et al., 2022; Saraswat et al., 2021). In this table the evaluation criteria are transferred to a common scale, highly suitable, suitable, moderately suitable, less suitable and not suitable.

Table 4.5: Veto criteria for location selection of PV-wind-energy storage projects (Aghaloo et al., 2023; Gao et al., 2022; Saraswat et al., 2021)

Criteria	Constraints	Illustration
Solar radiation (kWh/m^2/day)	<3.8	If the solar radiation is less than 3.8 then sufficient amount of power generation become difficult
Orientation (Facing direction)	North	North facing solar panels faces difficulties to generate sufficient amount of energy
Temperature (°C)	>34	High the temperature reduces the power from PV modules
Wind velocity (m/s)	<3	Below 3 m/s speed wind power is not appropriate for energy generation
DIF (Wh/m^2)	<2.4	Not suitable for PV energy generation
DNI (Wh/m^2)	<4.3	Not suitable for PV energy generation
Elevation (m)	>1500	Due to high altitude the installation of PV and wind power equipment is difficult. It increases the cost
Slope (%)	>3	The applicability is high if the slope is smaller
Aspect	>90	High slope is not suitable for energy production
Land use	It should not be mixed forest, dense agricultural land, housing construction and water bodies	The lower degree of development, the higher the suitability
Hill shade	Highly hilly region	Difficult to installed materials
Distance to the road network (km)	<500 m && >5	The distance between 500 m is unsuitable due to safety reason and the higher the distance from road it increases the difficulties of transportation
Distance from rail network (km)	<0.5 && >40	The lower the distance reduces the safety and higher the rail network distance increases the transportation cost
Distance to the water bodies (km)	<7	Area within 7 km is unsuitable for safety reason
Distance from Urban settlements (km)	<1	Below this distance the building the setup is not suitable due to safety
Distance from rural settlements (m)	<1 && >9	Lower distance is unsuitable due to safety reason and higher distance may cause difficulties in transmission losses
Distance from protected areas (km)	<2	Below this distance it is not suitable due to safety reason
Distance from transmission line (km)	>40	If the transmission line is greater in distance, it becomes difficult if the power need to sale to the grid

Distance from Power Plants (km)	<10	Less than the mentioned distance is not suitable for decentralized system

4.2.5 Decision making Process:

As there are conflicting evaluation criteria, the optimal location selection using decision-making process becomes critical and uncertain. To overcome this limitation, an improved and more accurate FLTS-MCDM approach, i.e., the NEAT-F-PROMETHEE method is used to find the solution. The advantage of this method over the classical fuzzy-MCDM approaches are discussed in references (Karam et al., 2020; Ziemba, 2021b). To evaluate the robustness of the obtained solution more efficient and precise MCDM methods, i.e., HFL-MCDM is used. The HFL-AHP and HFL-TOPSIS are used to estimate the criteria weights and to decide the alternative's rank respectively.

4.2.5.1 NEAT-F-PROMETHEE:

The NEAT-F-PROMETHEE method is a fuzzy outranking method that helps to decide the feasible solution under various uncertainty conditions. It is a relatively new method and proposed by Ziemba P (Ziemba, 2021a). It is successfully implemented to solve different MCDM problems under uncertainty conditions (Ziemba, 2021b). As this method belongs to a fuzzy group it considers the uncertainty of the input data and criteria weights. Due to the outranking behaviour, it considers the uncertainty, conflicts and the decision makers contradictions (Ziemba, 2021b). It also does not consider the dependencies between the criteria (Ziemba, 2021b, 2021a).. Beside analysing under uncertainty conditions the method also performs the analysis for crisp data which helps to obtain the decision-making solution easily with high precision (Ziemba, 2021b, 2021a).

This method considers the problem of fuzzy decision alternatives with order m. It belongs to the set A = {a, b, …,, m}. It also considers the criteria with n^{th} order which belongs to set C = {c_1, c_2, …, n}. This method considers the crisp (a_1=a_2=a_3=a_4), interval numbers (Ins) (a_1=a_2 and a_3=a_4), and trapezoidal fuzzy numbers (TFNs) (a_2=a_3). This TFN is the updated version of triangular fuzzy number (TrFNs) (Ziemba, 2021b). The process of this method is discussed in following steps:

1^{st} step: The decision alternatives for each criterion are assessed. In this step, numerical scale for certain criteria or linguistic scale can be used. The elements of both scales need to be expressed in the form TFNs. Additionally, the criteria are also assigned using a linguistic scale.

The linguistic scale for the decision alternatives and for the weights of the criteria is shown in Table 4.6 (Ziemba, 2021a).

Table 4.6: Linguistic scale in NEAT-F-PROMETHEE (Ziemba, 2021a):

Weight of the Criteria		**Alternative ranking**	
Linguistic Scale	TFNW = (w1, w2, w3, w4)	Linguistic scale	TFNA (a1, a2, a3, a4)
Very low	(0,0,0.1,0.2)	Very poor	(0,0,1,2)
Low	(0.1,0.2,0.2,0.3)	Poor	(1,2,2,3)
Medium low	(0.2,0.3,0.4,0.5)	Medium poor	(2,3,4,5)
Medium	(0.4,0.5,0.5,0.6)	Fair	(4,5,5,6)
Medium high	(0.5,0.6,0.7,0.8)	Medium good	(5,6,7,8)
High	(0.7,0.8,0.8,0.9)	Good	(7,8,8,9)
Very High	(0.8,0.9,1,1)	Very good	(8,9,10,10)

Subsequently, a pairwise comparison matrix of the alternatives is performed depending on the criteria. The fuzzy deviation d is calculated using Eq. 4.1(Ziemba, 2021b).

$$d_j(a, b) = c_j(a) \ominus c_j(b) \tag{4.1}$$

Where $c_j(a)$ is the fuzzy assessment of alternative "a" in terms of j = 1…n criterion.

Fuzzy deviation is expressed in the form of TFN is mapped to the form of uni-criterion preference degrees $P_j(d_j\ (a,b) \in [0,1]$. This mapping is performed using the mapping function f and it belongs to the 6-element set of mapping function $F = \{f_1, \ldots, f_n\}$. It is mainly used in the classical crisp PROMETHEE method and it is described using Eq. 4.2 (Ziemba, 2021b).

$$P_j\left(d_j(a, b)\right) = f_k[\, d_j(a, b)] \tag{4.2}$$

In the PROMETHEE family the following mapping functions f are distinguished and also referred to as a preference functions. These functions are the usual criterion, V-shaped criterion, U-shaped criterion, level criterion, Gaussian criterion etc. These preference functions are based on the indifference (q), preference (p) and the Gaussian (s) thresholds (Karam et al., 2020). The indifference determines the deviation between alternatives. It helps to consider that a weak preference relation takes place between them. The preference threshold estimates the value of deviation between alternatives and helps to determine the strict preference relation. The Gaussian threshold indicates the inflection point of the Gaussian curve.

This NEAT-F-PROMETHEE MCDM method assumes that the process of mapping must be verified and corrected. It reduces the approximation error which occurs during the TFNs mapping. The individual preference function along with the correction functions are implemented in this method.

2nd step: In this step, the weights of the criteria are de-fuzzified through the centroid method by using Eq. 4.3.

$$w_j(W_j) = \frac{w_{j3}^2 + w_{j4}^2 + w_{j3}w_{j4} - w_{j1}^2 + w_{j2}^2 + w_{j1}w_{j2}}{3(w_{j3} + w_{j4} - w_{j1} - w_{j2})} \tag{4.3}$$

Where the weights w_j (W_j) is the crisp number and represented by $w_{j1} = w_{j2} = w_{j3} = w_{j4}$.

The weights of the criteria are standardized to 1 in the form of crisp numbers and calculated on the basis of Eq. 4.4

$$w_j = \frac{w_j(W_j)}{\sum_{i=1}^{n} w_i(W_i)} \tag{4.4}$$

3rd step: The preferences P_j (d_j (a,b)) and the criteria weights w_j are aggregated into the form of global preference degrees and each pair of alternatives are in global order to the following expression shown in Eq. 4.5.

$$\pi(a,b) = \sum_{j=1}^{n} P_j\left(d_j(a,b)\right) \times w_j \tag{4.5}$$

Where π (a, b) takes the value in the range of [0,1] as similar to the P_j (d_j (a,b)). These values determine the global order of each pair of the alternatives that are used in the system of preference relations.

4th step: After performing the global ordering of alternatives, fuzzy positive and negative outranking flows are calculated by using Eqs. 4.6 and 4.7.

$$\emptyset^+(a) = \frac{\sum_{i=1}^{m} \pi(a,b_i)}{m-1} \tag{4.6}$$

$$\emptyset^-(a) = \frac{\sum_{i=1}^{m} \pi(b_i,a)}{m-1} \tag{4.7}$$

By using these outranking flows global ranking of alternatives is developed in the NEAT-F-PROMETHEE I method and used to calculate the net fuzzy outranking flow in the NEAT-F-PROMETHEE II method by using Eq. 4.8.

$$\emptyset_{net}(a) = \emptyset^+(a) \ominus \emptyset^-(a) \tag{4.8}$$

6th Step; In this step, fuzzy positive, negative and net outranking flow are de-fuzzified to estimate the crisp ranking by using Eqs. 4.9-4.11

$$\phi_c^+(a) = \frac{\phi^+(a)_3^2 + \phi^+(a)_4^2 + \phi^+(a)_4\phi^+(a)_3 - \phi^+(a)_1^2 + \phi^+(a)_2^2 + \phi^+(a)_1\phi^+(a)_2}{3(\phi^+(a)_4 + \phi^+(a)_3 - \phi^+(a)_1 - \phi^+(a)_2)} \tag{4.9}$$

$$\phi_c^-(a) = \frac{\phi^-(a)_3^2 + \phi^-(a)_4^2 + \phi^-(a)_4\phi^-(a)_3 - \phi^-(a)_1^2 + \phi^-(a)_2^2 + \phi^-(a)_1\phi^-(a)_2}{3(\phi^-(a)_4 + \phi^-(a)_3 - \phi^-(a)_1 - \phi^-(a)_2)} \tag{4.10}$$

$$\phi_{netc}(a) = \frac{\phi_{net}(a)_3^2 + \phi_{net}(a)_4^2 + \phi_{net}(a)_3\phi_{net}(a)_4 - \phi_{net}(a)_1^2 - \phi_{net}(a)_2^2 - \phi_{net}(a)_2\phi_{net}(a)_1}{3(\phi_{net}(a)_3 - \phi_{net}(a)_4 - \phi_{net}(a)_2 - \phi_{net}(a)_1)} \tag{4.11}$$

7th step: By using the following preference equations the partial order of the alternatives in NEAT-F-PROMETHEE I is determined.

8th step: Finally, the total order of alternatives in NEAT-F-PROMETHEE II is determined by using the preference relations.

4.2.6 Sensitivity analysis:

To evaluate the robustness and the consistency of the obtained solution the sensitivity analysis is performed. In this analysis a more precise linguistic approach, i.e., HFLTS-MCDM method is employed. In this study HFL-AHP is used to estimate the criteria weights and to decide the alternative's rank the HFL-TOPSIS method is used. The details of these methods are discussed in Chapter 3 under Sec. 3.2.3.

4.3 Results and Discussions:

The study is aimed to decide an optimal feasible location for developing decentralized HES.

4.3.1 Evaluation criteria and data collection:

Total 19 evaluation criteria are considered to decide the best location. The evaluation criteria data for different locations are assessed through the GIS tool.

4.3.1.1 Resource factors:

The visible spectrum of solar irradiation (GHI), normal irradiation (DNI) and global diffuse horizontal irradiance (DIF) are important for selecting sites to develop solar based hybrid energy systems. The proposed methodology is demonstrated with the data of a state of Madhya Pradesh, India. The GHI, DNI and DIG are shown in Figs. 4.4. (a-c). The detailed data are mentioned in Table 4.7. According to the table it varies in the range of 5.2-5.44 kWh/m^2/day for the considered alternatives. The DIF is maximum and minimum for A8 (2.57 kWh/m^2/day) and A2 (2.41 kWh/m^2/day) respectively. The DNI is maximum and minimum for the location of A2 (4.62 kWh/m^2/day) and A1 (3.61 kWh/m^2/day).

Wind speed of the study area is shown in Fig. 4.4.d. The wind speed value is provided in Table 4.7. According to the table the wind speed varies 4.44 m/s-5.54 m/s.

Orientation of the solar PV panel is an important factor to decide the location.The details of the PV panel orientation is described in Table 4.7. South and flat oriented PV panels are obtained for the location of A5 and A9 respectively and North orientation is obtained for the location of A1.

4.3.1.2 Climatic factor:

Temperature is considered under the climatic factor and it is shown in Fig. 4.4.e. The detailed temperature of 9 locations are shown in Table 4.7. The temperature of the considered location varies in the range 23.96ºC (A7)- 26.64ºC (A1).

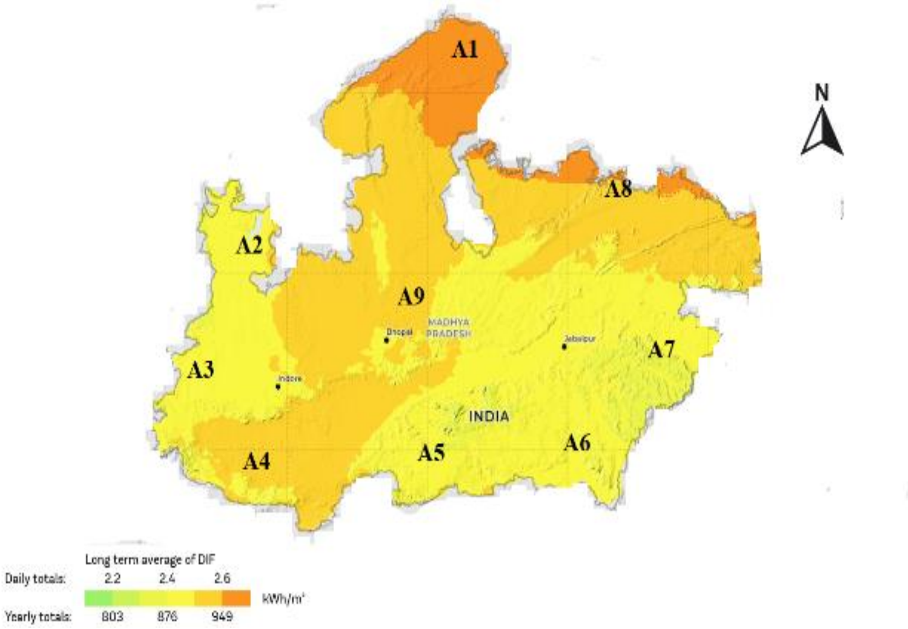
4.3.1.3 Topographic factors:

Elevation, slope, aspect and hill shade are the four major geographical aspects that have significant impact on developing decentralized HESs are shown in Figs. 4.4.f-i. The data is provided in Table 4.7. The elevation and aspect are 825 m and 95 m respectively which are observed for location A6. Elevation and aspect are minimum for location A8 (128 m) and A9 (28 m) respectively. The slopes of these 9 alternatives vary between 0-3%. Location A1 and A8 are low land according to the analysis.

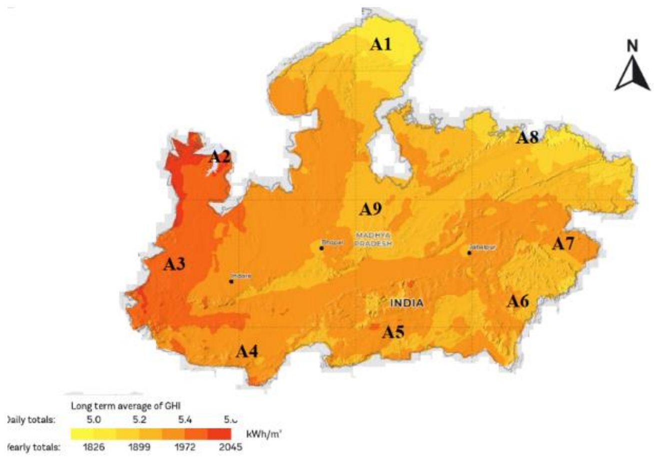
4.3.1.4 Economic factors:

The economic factors are shown in Figs. 4.4.j-n and the data is provided in Table 4.7. The files are in shape file format. The table shows that location A1 and A9 are nearer to the road (1.3 km) and railway network (12 km) respectively. Among the locations A9, A2, and A8 are crop land (moderately suitable), A3 is grassland (suitable), A4 and A7 are barren land (highly suitable) and other locations are mixed forest areas which are not suitable. Location A6 is closer to rural areas and the distance of location A3 is higher from it. Location A7 is at a maximum distance from the urban areas.

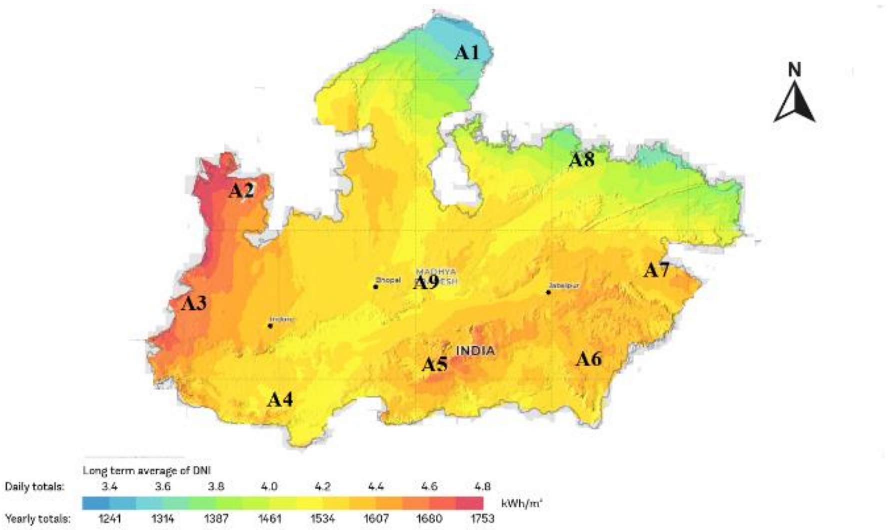
a


N
A1
A2
A3
A4
A5
A6
A7
A8
A9
MADHYA PRADESH
INDIA
Bhopal
Indore
Jabalpur
Long term average of DIF
Daily totals: 2.2 2.4 2.6
kWh/m²
Yearly totals: 803 876 949

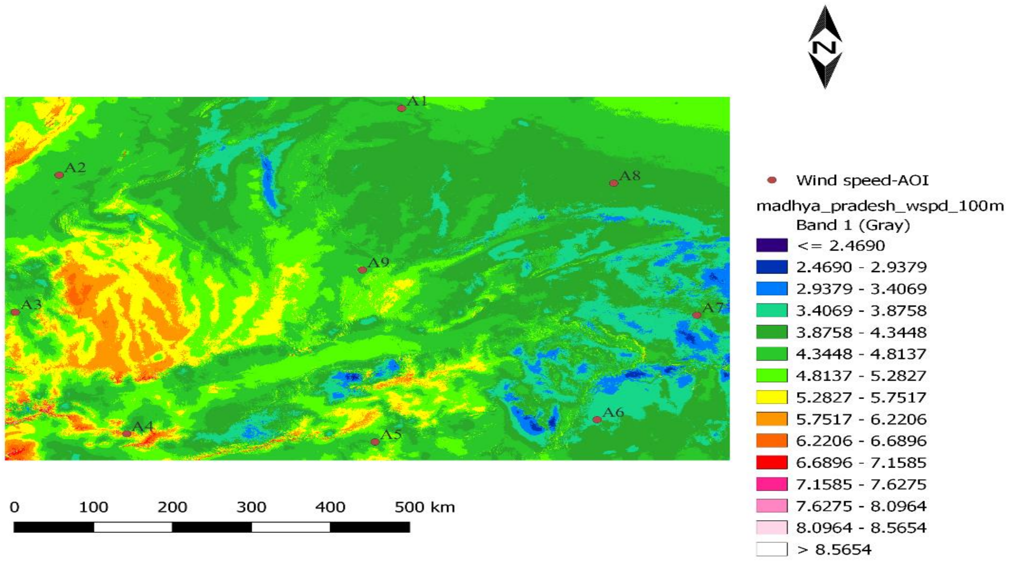
b


N
A1
A2
A3
A4
A5
A6
A7
A8
A9
MADHYA PRADESH
INDIA
Long term average of GHI
Daily totals: 5.0 5.2 5.4
kWh/m²
Yearly totals: 1826 1899 1972 2045

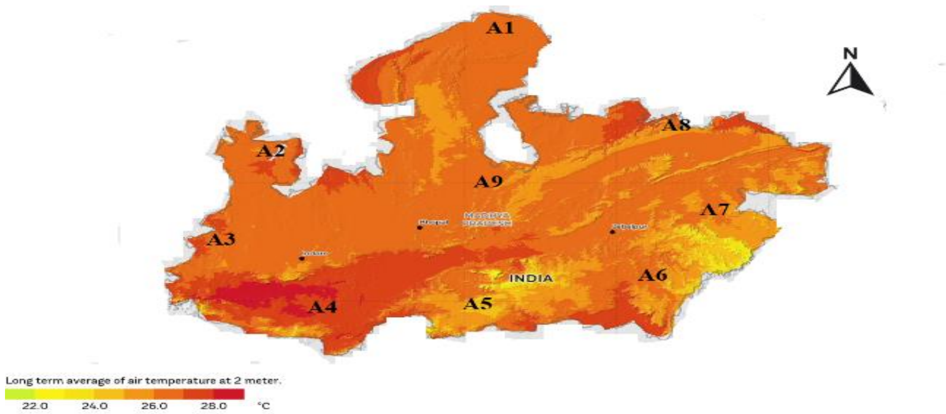
c


N
A1
A2
A3
A4
A5
A6
A7
A8
A9
MADHYA PRADESH
INDIA
Bhopal
Indore
Jabalpur
Long term average of DNI
Daily totals: 3.4 3.6 3.8 4.0 4.2 4.4 4.6 4.8
kWh/m²
Yearly totals: 1241 1314 1387 1461 1534 1607 1680 1753

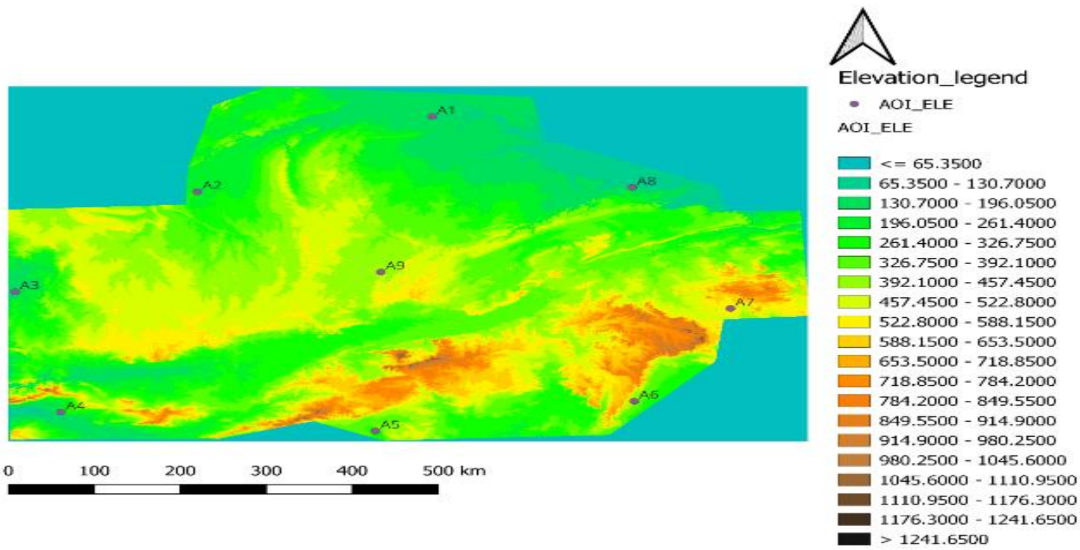
d


A1
A2
A8
A9
A3
A7
A4
A5
A6
N
Wind speed-AOI
madhya_pradesh_wspd_100m
Band 1 (Gray)
<= 2.4690
2.4690 - 2.9379
2.9379 - 3.4069
3.4069 - 3.8758
3.8758 - 4.3448
4.3448 - 4.8137
4.8137 - 5.2827
5.2827 - 5.7517
5.7517 - 6.2206
6.2206 - 6.6896
6.6896 - 7.1585
7.1585 - 7.6275
7.6275 - 8.0964
8.0964 - 8.5654
> 8.5654
0 100 200 300 400 500 km

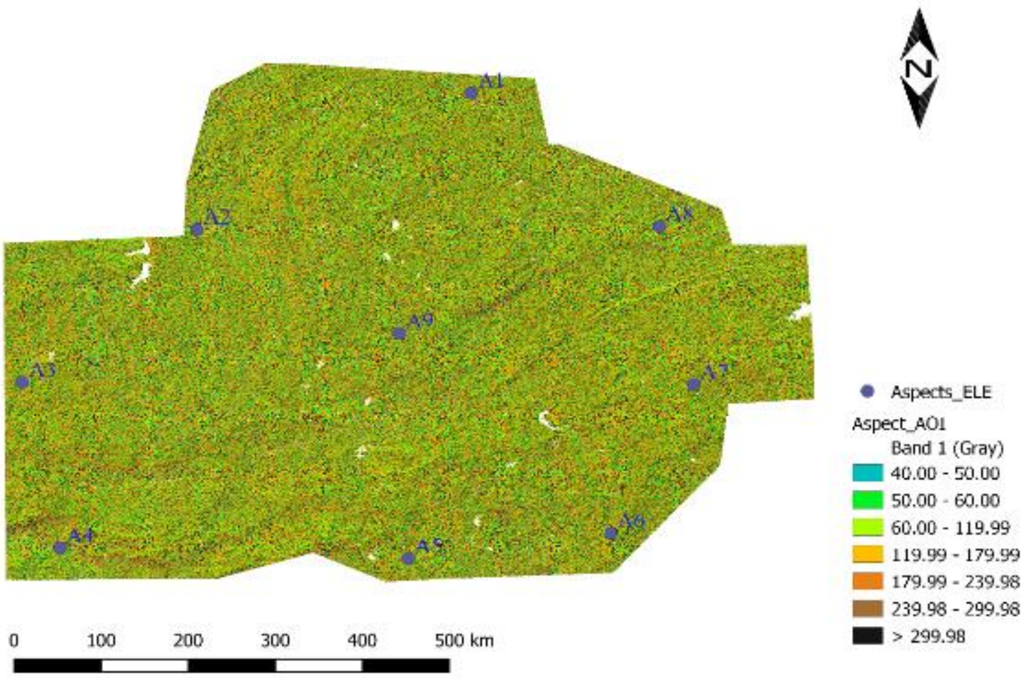
e


A1
A2
A8
A9
A7
A3
A6
INDIA
A4
A5
N
Long term average of air temperature at 2 meter.
22.0 24.0 26.0 28.0 °C

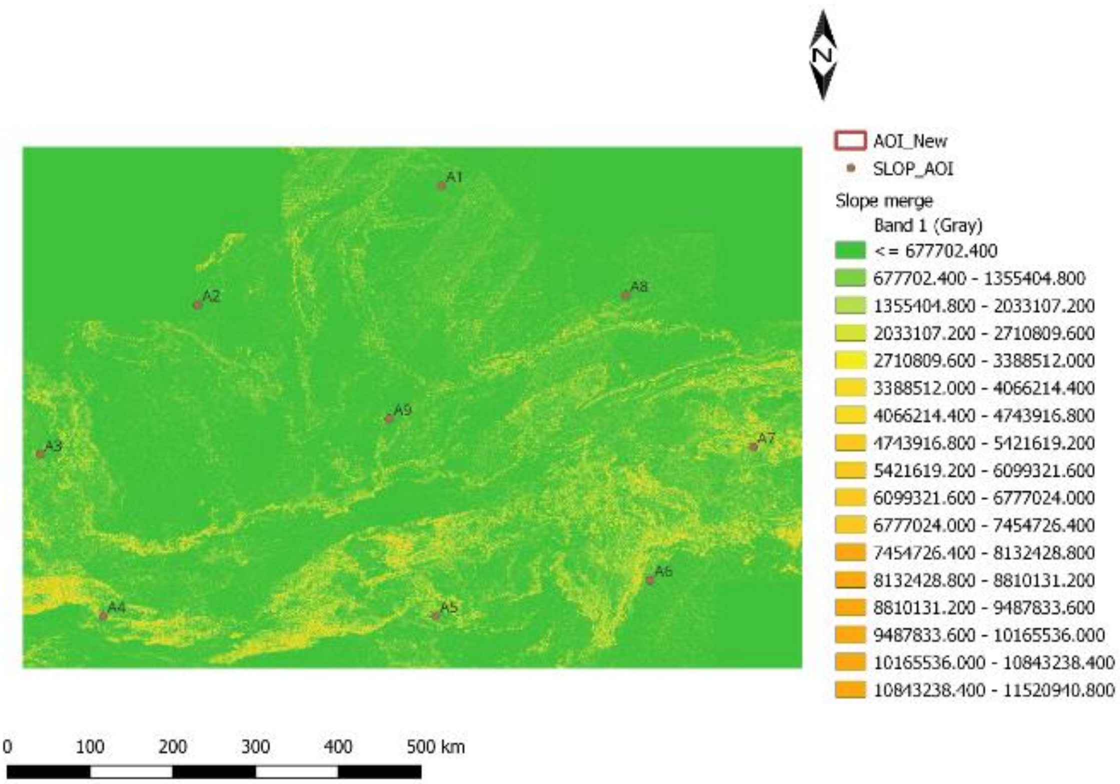
f


Elevation_legend
AOI_ELE
AOI_ELE
<= 65.3500
65.3500 - 130.7000
130.7000 - 196.0500
196.0500 - 261.4000
261.4000 - 326.7500
326.7500 - 392.1000
392.1000 - 457.4500
457.4500 - 522.8000
522.8000 - 588.1500
588.1500 - 653.5000
653.5000 - 718.8500
718.8500 - 784.2000
784.2000 - 849.5500
849.5500 - 914.9000
914.9000 - 980.2500
980.2500 - 1045.6000
1045.6000 - 1110.9500
1110.9500 - 1176.3000
1176.3000 - 1241.6500
> 1241.6500
A1
A2
A8
A9
A3
A7
A6
A4
A5
0 100 200 300 400 500 km

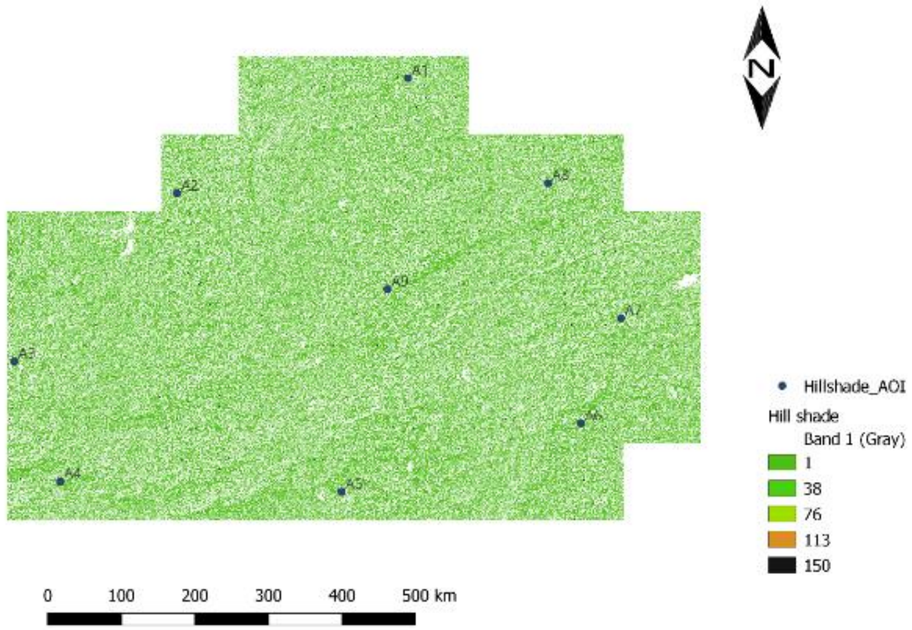
g


A1
A2
A8
A9
A3
A7
A6
A4
A5
N
Aspects_ELE
Aspect_AOI
Band 1 (Gray)
40.00 - 50.00
50.00 - 60.00
60.00 - 119.99
119.99 - 179.99
179.99 - 239.98
239.98 - 299.98
> 299.98
0 100 200 300 400 500 km

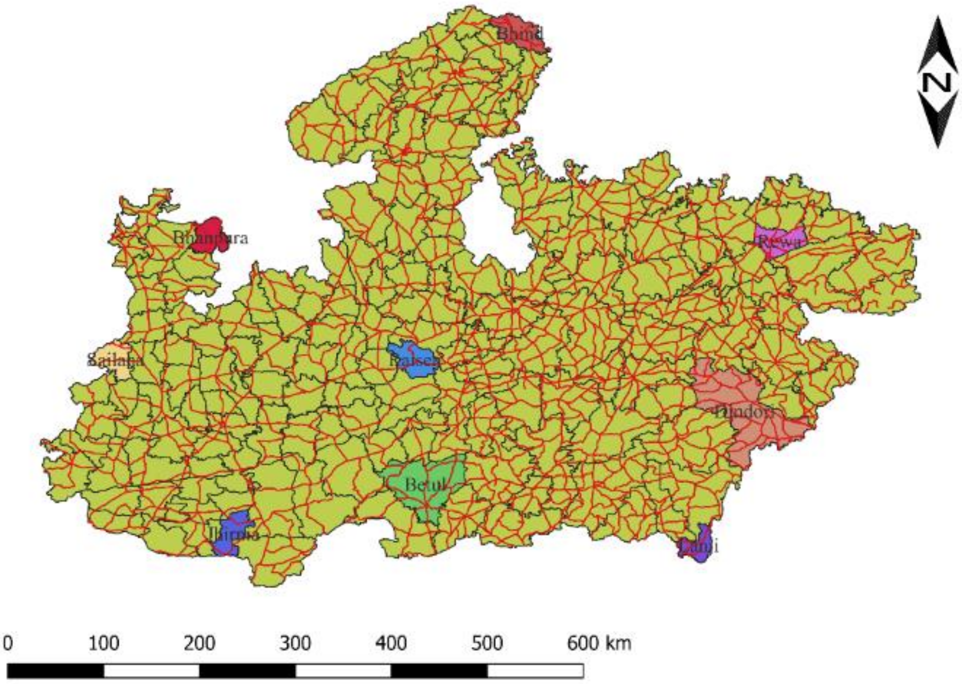
h


N
AOI_New
SLOP_AOI
Slope merge
Band 1 (Gray)
<= 677702.400
677702.400 - 1355404.800
1355404.800 - 2033107.200
2033107.200 - 2710809.600
2710809.600 - 3388512.000
3388512.000 - 4066214.400
4066214.400 - 4743916.800
4743916.800 - 5421619.200
5421619.200 - 6099321.600
6099321.600 - 6777024.000
6777024.000 - 7454726.400
7454726.400 - 8132428.800
8132428.800 - 8810131.200
8810131.200 - 9487833.600
9487833.600 - 10165536.000
10165536.000 - 10843238.400
10843238.400 - 11520940.800
A1
A2
A8
A9
A3
A7
A6
A4
A5
0 100 200 300 400 500 km

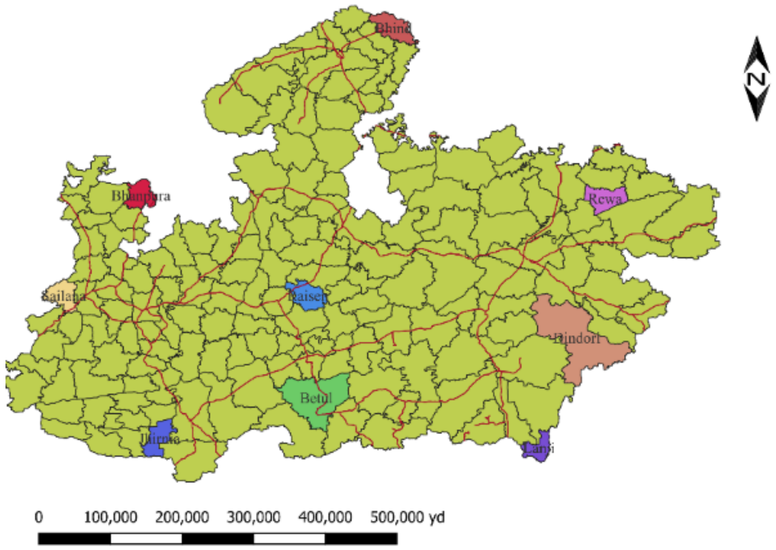
i


N
A1
A2
A3
A4
A5
A6
A7
A8
A9
Hillshade_AOI
Hill shade
Band 1 (Gray)
1
38
76
113
150
0
100
200
300
400
500 km

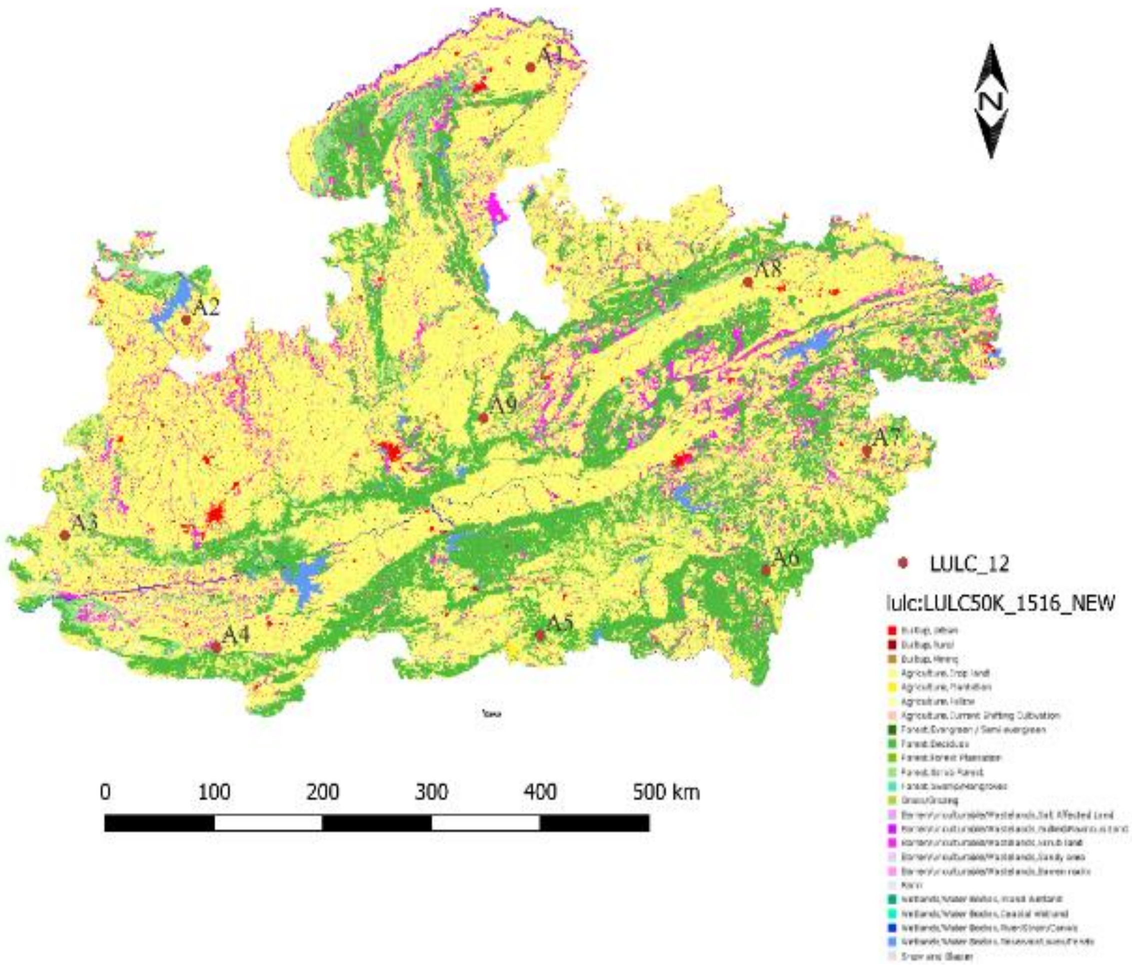
j


Bhind
Rewa
Betul
N
0
100
200
300
400
500
600 km

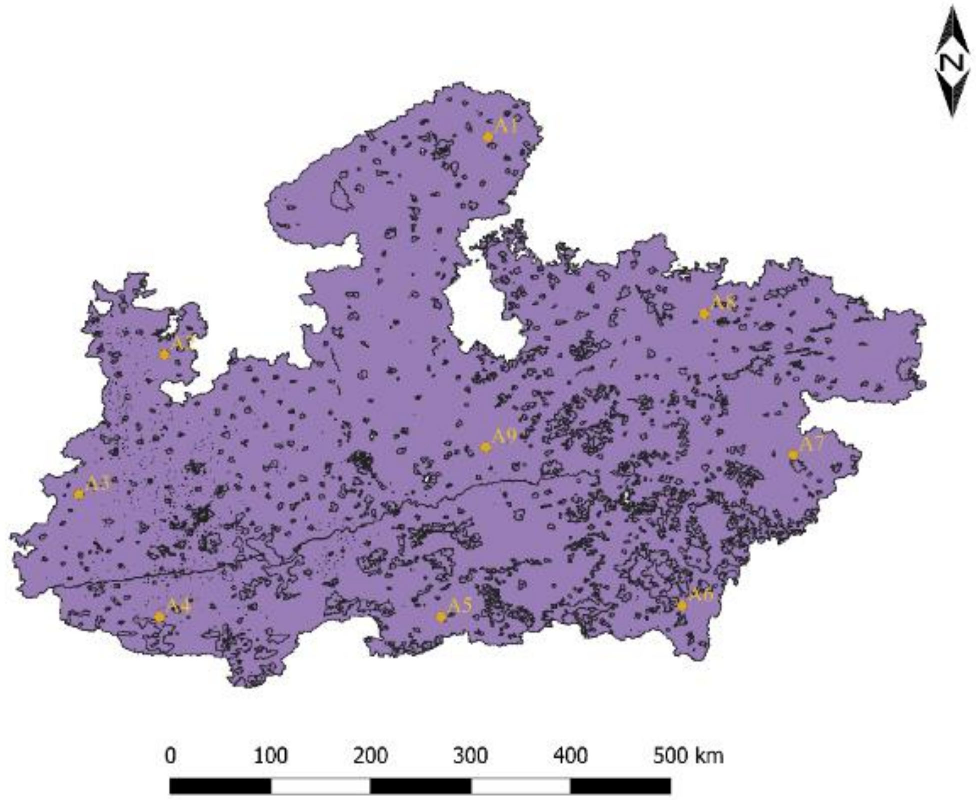
k


Bhind
Rewa
Raisen
Dindori
Betul
N
0 100,000 200,000 300,000 400,000 500,000 yd

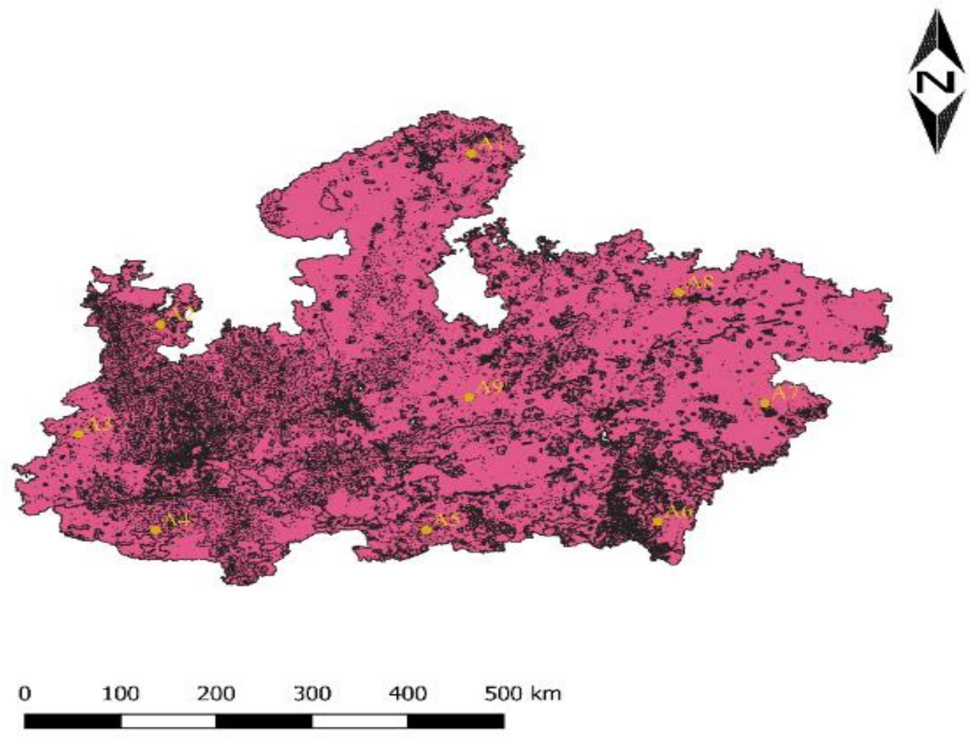
l


A1
A2
A3
A4
A5
A6
A7
A8
A9
N
LULC_12
lulc:LULC50K_1516_NEW
0 100 200 300 400 500 km

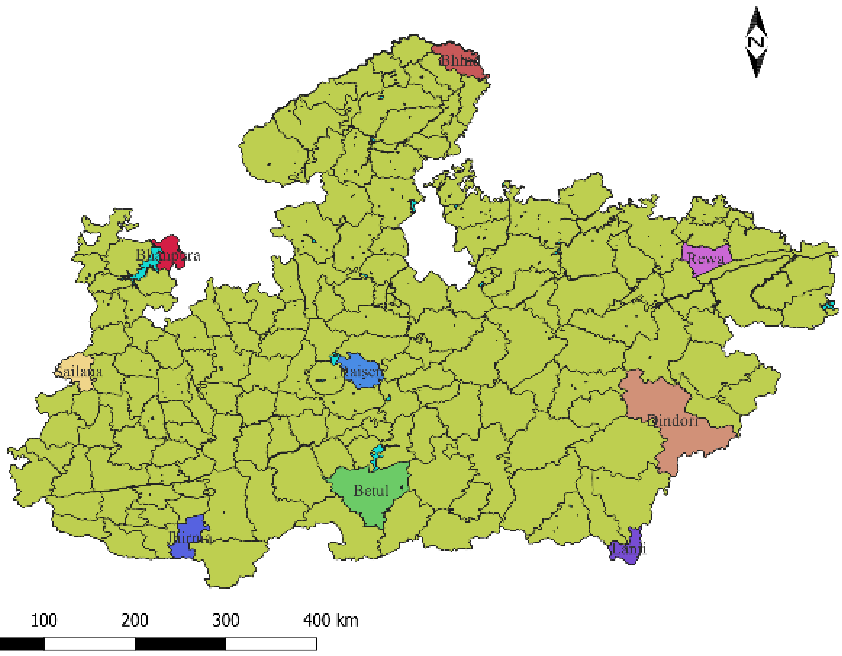
m


N
A1
A2
A3
A4
A5
A6
A7
A8
A9
0
100
200
300
400
500 km

n

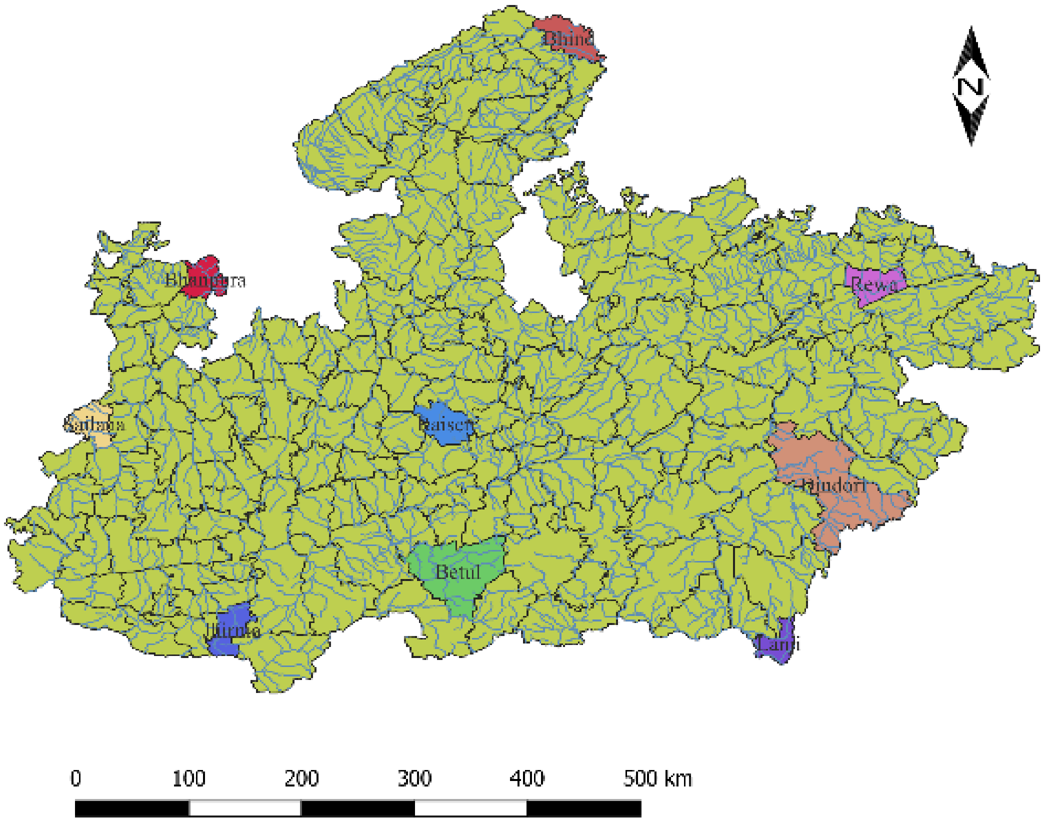

N
A1
A2
A3
A4
A5
A6
A7
A8
A9
0
100
200
300
400
500 km

o



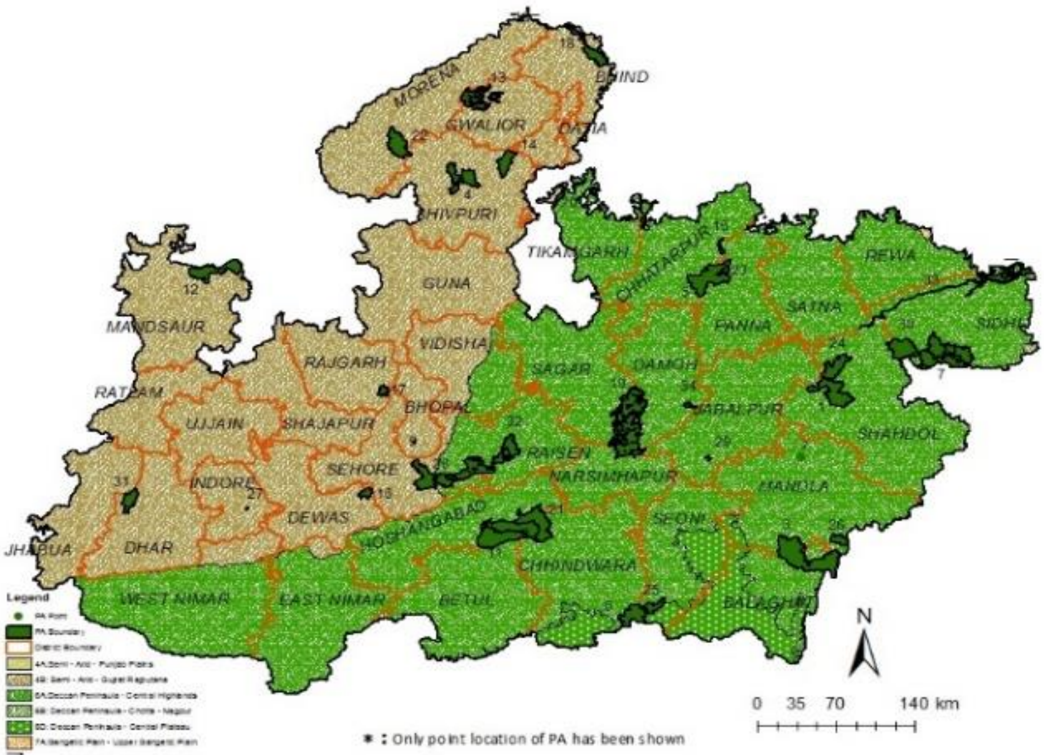
N
Rewa
Betul
Dindori
0
100
200
300
400 km

p



N
Bhind
Rewa
Betul
Dindori
Lanji
0
100
200
300
400
500 km

q



r

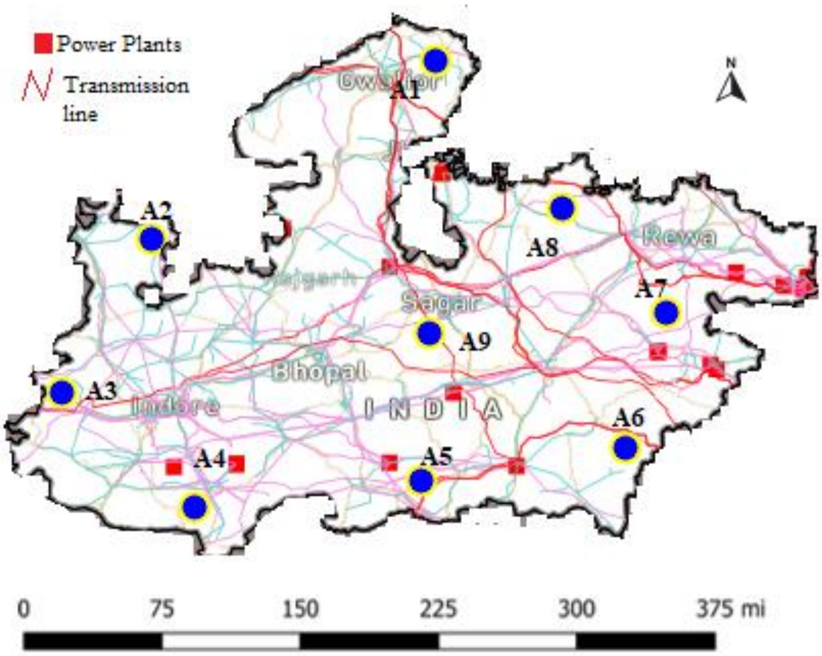


Fig. 4.4. a) Solar GHI, b) DIF, c) DNI, d) wind speed, e) temperature, f) Elevation, g) slope, h) aspect, i) hillshade, j) Road distribution, k) Railway distribution, l) Land use, m) Rural distribution, n) Urban distribution, o) water bodies of the locations, p) water lines, q) protected areas, r) transmission and power plants

4.3.1.5 Social factors:

The social factors are shown in Fig. 4.4.o-r. The data is provided in Table 4.7. Location A5 is located at the maximum distance from the water bodies (62.8 km). Location A2 is the nearest location of the protected areas (8 km). The transmission lines and power plants distance from each location are in moderate distance.

No single best suitable location is obtained through these evaluation criteria data. The decision-making approach is hence integrated with the GIS tool to decide the acceptable best location for the projects.

Table 4.7: Data for alternatives

Criteria	A1	A2	A3	A4	A5	A6	A7	A8	A9
Solar radiation (kWh/m^2/day)	5.25	5.44	5.31	5.31	5.33	5.2	5.22	5.28	5.27
Orientation (Facing direction)	North	North west	West	South west	South	South east	East	North east	Flat
Temperature (ºC)	26.64	25.88	25.83	25.55	25.35	25.58	23.96	26	25.49
Wind velocity (m/s)	4.44	4.94	5.54	4.45	5.14	4.54	4.68	4.46	5.02
DIF (kWh/m^2/day)	2.7	2.41	2.5	2.56	2.45	2.4	2.43	2.57	2.5
DNI (kWh/m^2/day)	3.61	4.62	4.6	4.12	4.43	4.4	4.39	3.8	4.39
Elevation (m)	144	346	276	433	441	825	450	125	548
Slope (%)	1.98	0	0.28	1	1.2	3	2.6	1.8	1.39
Aspect (m)	212	63	74	45	26	95	78	91	28
Land use	Crop land	Crop land	Grass land	Barren land	Forest plantation	Forest plantation	Barren land	Crop land	Forest land
Hill shade	Low land	Medium high	Medium low	High land	High land	Very high	High land	Low land	High land
Distance to the road network (km)	1.3	1.8	2.7	3.19	4.12	1.945	2	4.45	1.36
Distance from rail network (km)	35	18	28	62	10	32	55	42	12
Distance to the water bodies (km)	43.7	10.23	44.12	10.89	62.79	53.12	55.26	46.2	21.28
Distance from Urban settlements (km)	8.9	12.319	12.69	9.54	9.2	3.23	12.87	11.1	13.51

Distance from rural settlements (m)	1.34	0.88	4.77	1	1.53	0.46	0.94	1.36	4.28
Distance from protected areas (km)	10.37	8.01	33.3	45.4	11.47	18.37	26.66	32.37	10.88
Distance from transmission line (km)	6.13	7.87	5.6	10.55	5.48	16.66	15.45	9.21	11.23
Distance from Power Plants (km)	110	94	56	42	38	124	69	44	41.23

4.3.2 Ranking of the alternatives:

The decision-making process for selecting location based on the evaluation criteria is complex and uncertain. It becomes difficult for the decision makers to decide the best location through crisp values. The fuzzy MCDM approach gives the decision makers more flexibility by providing a large set of linguistic variables. The linguistic scale is assigned by the pool of decision-makers. These decision makers are selected from different backgrounds. In this fuzzy approach first the weights of the criteria are determined and then using the weights the net ranking is decided. It also gives a crisp ranking. Using the linguistic variable set, decision makers develop the decision matrix for both the evaluation criteria and the data of these criteria for each alternative. Then the linguistic variables are converted into fuzzy numbers. Using this matrix, the decision-making analysis is performed through this process. Table 4.8 shows the linguistic term set and fuzzy number of the criteria. Tables 4.9 and 4.10 are the linguistic and fuzzy number table of evaluation criteria data for each alternative respectively.

Table 4.8: Linguistic term set and fuzzy number for NEAT-F-PROMETHEE

Criteria	Linguistic scale	Fuzzy number
Solar radiation (kWh/m^2/day)- C11	Very high	(0.8,0.9,1,1)
Wind velocity (m/s)-C12	Very high	(0.8,0.9,1,1)
DNI (kWh/m^2/day)- C13	ML	(0.2,0.3,0.4,0.5)
DIF (kWh/m^2/day)- C14	ML	(0.2,0.3,0.4,0.5)
Orientation (Facing direction)- C15	MH	(0.5,0.6,0.7,0.8)
Temperature (ºC)- C21	MH	(0.5,0.6,0.7,0.8)
Elevation (m)-C31	MH	(0.5,0.6,0.7,0.8)
Slope (%)-C32	ML	(0.2,0.3,0.4,0.5)
Aspect (m)-C33	ML	(0.2,0.3,0.4,0.5)
Hill shade-C34	M	(0.4,0.5,0.5,0.6)
Distance to the road network (km)- C41	H	(0.7,0.8,0.8,0.9)
Distance from rail network (km)- C42	MH	(0.5,0.6,0.7,0.8)
Distance from Urban settlements (km)- C43	MH	(0.5,0.6,0.7,0.8)
Distance from rural settlements (m)- C44	H	(0.7,0.8,0.8,0.9)
Land use- C45	H	(0.7,0.8,0.8,0.9)
Distance from transmission line (km)- C46	ML	(0.2,0.3,0.4,0.5)
Distance to the waterbodies (km)- C51	Very high	(0.8,0.9,1,1)
Distance from protected areas (km)- C52	MH	(0.5,0.6,0.7,0.8)
Distance from Power Plants (km)- C53	ML	(0.2,0.3,0.4,0.5)

Then the net outrank flow is estimated. Finally, the fuzzy values are defuzzified and shown in Table 4.11. This table also shows the rank of the alternatives based on these defuzzified values of the outranking flow. Net fuzzy and crisp outranking flow is shown in Fig. 4.5. This describes the balance between positive and negative outranking flows with a net outranking flow that indicates a better alternative. The partial order of the alternatives is estimated using NEAT-Fuzzy-PROMETHEE I method and it is shown in Fig. 4.6. Partial order of alternatives shows that A3 is the best location followed by A2, A4 and A6. After A6 both the locations A9 and A1 can get the priority. The same priority is obtained for A5 and A8. The preference for these locations is almost equal. Any of these are eligible to get the priority. However, the least acceptable location is A7.

Table 4.9: Linguistic term set for ranking analysis through NEAT-F-PROMETHEE

Alternatives	**C11**	**C12**	**C13**	**C14**	**C15**	**C21**	**C31**	**C32**	**C33**	**C34**	**C41**	**C42**	**C43**	**C44**	**C45**	**C46**	**C51**	**C52**	**C53**
A1	F	F	VP	VG	VP	VP	G	F	VP	VG	VG	MP	F	VG	F	G	G	F	VG
A2	VG	G	G	P	P	F	F	VG	F	F	G	G	G	P	F	MG	P	P	VG
A3	MG	VG	MG	F	F	F	MG	VG	F	G	MG	MG	VG	G	MG	VG	G	VG	G
A4	MG	F	P	G	G	G	MP	G	G	P	F	VP	MP	G	VG	F	P	VG	MG
A5	G	VG	F	F	VG	MG	P	G	VG	P	MP	VG	MP	VG	MP	VG	VG	F	F
A6	P	F	F	MP	G	G	VP	VP	P	VP	G	F	P	VP	MP	MP	G	MG	VG
A7	P	MG	P	F	F	VG	P	P	F	MP	G	VP	F	P	VG	P	G	G	G
A8	F	F	VP	G	P	P	VG	MG	MP	VG	P	P	G	VG	F	F	G	VG	MG
A9	F	G	MP	MG	VG	MG	P	G	VG	P	VG	VG	VG	G	P	F	F	F	F

Table 4.10: Fuzzy number alternative data for NEAT-F-PROMETHEE

Alternatives	C11	C12	C13	C14	C15	C21	C31	C32	C33	C34	C41	C42	C43	C44	C45	C46	C51	C52	C53
A1	(4,5,5,6)	(4,5,5,6)	(0,0,1,2)	(8,9,10,10)	(0,0,1,2)	(0,0,1,2)	(7,8,8,9)	(4,5,5,6)	(0,0,1,2)	(8,9,10,10)	(8,9,10,10)	(2,3,4,5)	(4,5,5,6)	(8,9,10,10)	(4,5,5,6)	(7,8,8,9)	(7,8,8,9)	(4,5,5,6)	(8,9,10,10)
A2	(8,9,10,10)	(7,8,8,9)	(7,8,8,9)	(1,2,2,3)	(1,2,2,3)	(4,5,5,6)	(4,5,5,6)	(8,9,10,10)	(4,5,5,6)	(4,5,5,6)	(7,8,8,9)	(7,8,8,9)	(7,8,8,9)	(1,2,2,3)	(4,5,5,6)	(5,6,7,8)	(1,2,2,3)	(1,2,2,3)	(8,9,10,10)
A3	(5,6,7,8)	(8,9,10,10)	(5,6,7,8)	(4,5,5,6)	(4,5,5,6)	(4,5,5,6)	(5,6,7,8)	(8,9,10,10)	(4,5,5,6)	(7,8,8,9)	(5,6,7,8)	(5,6,7,8)	(8,9,10,10)	(7,8,8,9)	(5,6,7,8)	(8,9,10,10)	(7,8,8,9)	(8,9,10,10)	(7,8,8,9)
A4	(5,6,7,8)	(4,5,5,6)	(1,2,2,3)	(7,8,8,9)	(7,8,8,9)	(7,8,8,9)	(2,3,4,5)	(7,8,8,9)	(7,8,8,9)	(1,2,2,3)	(4,5,5,6)	(0,0,1,2)	(2,3,4,5)	(7,8,8,9)	(8,9,10,10)	(4,5,5,6)	(1,2,2,3)	(8,9,10,10)	(5,6,7,8)
A5	(7,8,8,9)	(8,9,10,10)	(4,5,5,6)	(4,5,5,6)	(8,9,10,10)	(5,6,7,8)	(1,2,2,3)	(7,8,8,9)	(8,9,10,10)	(1,2,2,3)	(2,3,4,5)	(8,9,10,10)	(2,3,4,5)	(8,9,10,10)	(2,3,4,5)	(8,9,10,10)	(8,9,10,10)	(4,5,5,6)	(4,5,5,6)
A6	(1,2,2,3)	(4,5,5,6)	(4,5,5,6)	(2,3,4,5)	(7,8,8,9)	(7,8,8,9)	(0,0,1,2)	(0,0,1,2)	(1,2,2,3)	(0,0,1,2)	(7,8,8,9)	(4,5,5,6)	(1,2,2,3)	(0,0,1,2)	(2,3,4,5)	(2,3,4,5)	(7,8,8,9)	(5,6,7,8)	(8,9,10,10)
A7	(1,2,2,3)	(5,6,7,8)	(1,2,2,3)	(4,5,5,6)	(4,5,5,6)	(8,9,10,10)	(1,2,2,3)	(1,2,2,3)	(4,5,5,6)	(2,3,4,5)	(7,8,8,9)	(0,0,1,2)	(4,5,5,6)	(1,2,2,3)	(8,9,10,10)	(1,2,2,3)	(7,8,8,9)	(7,8,8,9)	(7,8,8,9)
A8	(4,5,5,6)	(4,5,5,6)	(0,0,1,2)	(7,8,8,9)	(1,2,2,3)	(1,2,2,3)	(8,9,10,10)	(5,6,7,8)	(2,3,4,5)	(8,9,10,10)	(1,2,2,3)	(1,2,2,3)	(7,8,8,9)	(8,9,10,10)	(4,5,5,6)	(4,5,5,6)	(7,8,8,9)	(8,9,10,10)	(5,6,7,8)
A9	(4,5,5,6)	(7,8,8,9)	2,3,4,5)	(5,6,7,8)	(8,9,10,10)	(5,6,7,8)	(1,2,2,3)	(7,8,8,9)	(8,9,10,10)	(1,2,2,3)	(8,9,10,10)	(8,9,10,10)	(8,9,10,10)	(7,8,9,9)	(1,2,2,3)	(4,5,5,6)	(4,5,5,6)	(4,5,5,6)	(4,5,5,6)

Table 4.11: Defuzzified outranking flow

Alternative	Net outranking flow (ϕ_{netc})	Complete Rank	Positive outranking flow (ϕ_c^+)	Partial Rank	Negative outranking flow (ϕ_c^-)	Partial Rank
A1	-0.0127	6	0.2349	5	0.2474	6
A2	0.0372	2	0.2555	2	0.2182	2
A3	0.0537	1	0.2621	1	0.2084	1
A4	0.0233	3	0.2524	3	0.2291	3
A5	-0.0350	8	0.2158	8	0.2509	7
A6	0.0168	4	0.2458	4	0.2291	4
A7	-0.0482	9	0.2147	9	0.2628	9
A8	-0.0341	7	0.2205	7	0.2546	8
A9	-0.0017	5	0.2345	6	0.2360	5

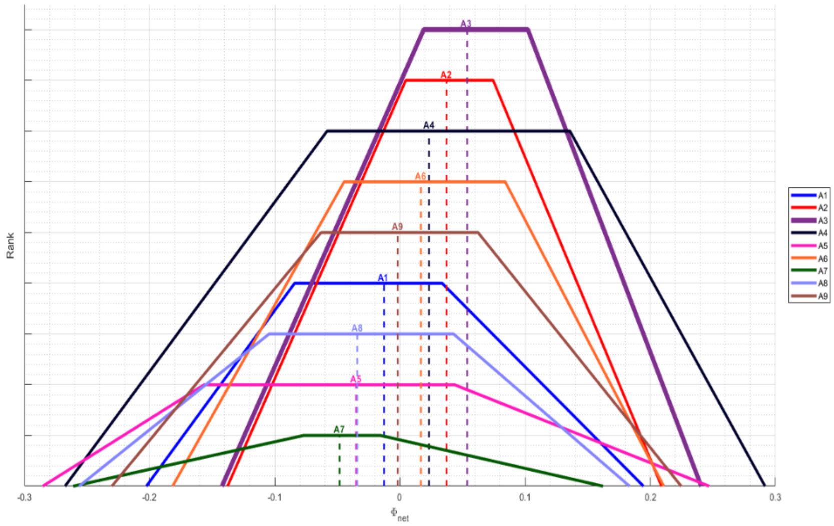


Fig. 4.5: Net Fuzzy and crisp outranking flow

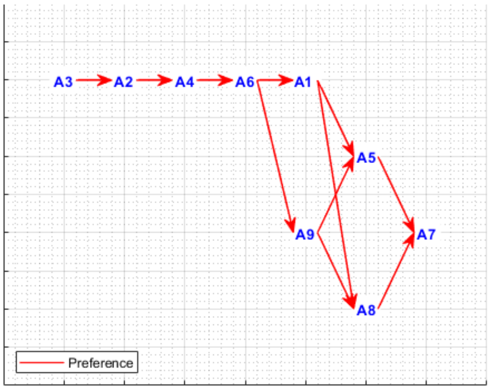


Fig. 4.6. Partial order preference

To validate the obtained ranking of the alternatives through this Fuzzy-MCDM approach, a more accurate MCDM approach, i.e., HFL-AHP and HFL-TOPSIS methods are jointly used. The detailed analysis results are discussed next.

4.3.3 Sensitivity analysis:

This sensitivity analysis is essential to evaluate the robustness and consistency of the obtained solution. The weights are estimated using the HFL-AHP method and by using these weights the ranking is decided by the HFL-TOPSIS method.

4.3.3.1 Determination of weights:

In the HFL-AHP method the weights of the criteria are calculated. In this method the criteria are transformed into linguistic variables on the basis of their importance by the decision-makers. The corresponding fuzzy numbers are also provided for the criteria. The linguistic term and each fuzzy number for the criteria is shown in Table 4.12.

Table 4.12: Weight calculation of the criteria using HFL-AHP

Criteria	Linguistic scale	Fuzzy number
Solar radiation (kWh/m^2/day)-C11	DHI	(7,9,9)
Wind velocity (m/s)-C12	DHI	(7,9,9)
DNI (kWh/m^2/day)- C13	ELI	(0.33,1,1)
DIF (kWh/m^2/day)- C14	ELI	(0.33,1,1)
Orientation (Facing direction)-C15	WHI	(1,3,5)
Temperature (°C)- C21	EHI	(1,1,3)
Elevation (m)-C31	EHI	(1,1,3)
Slope (%)-C32	WLI	(0.2,0.33,1)
Aspect (m)-C33	WLI	(0.2,0.33,1)
Hill shade-C34	EE	(1,1,1)
Distance to the road network (km)-C41	ESHI	(3,5,7)
Distance from rail network (km)-C42	WHI	(1,3,5)
Distance from Urban settlements (km)- C43	EHI	(1,1,3)
Distance from rural settlements (m)- C44	ESHI	(3,5,7)
Land use- C45	ESHI	(3,5,7)
Distance from transmission line (km)- C46	WLI	(0.2,0.33,1)
Distance to the waterbodies (km)-C51	EXHI	(5,7,9)
Distance from protected areas (km)- C52	ESHI	(3,5,7)
Distance from Power Plants (km)-C53	WLI	(0.2,0.33,1)

Considering this data, the weights are calculated through developing the pairwise comparison matrix of the criteria. The weights of the criteria are shown in Fig. 4.7. According to the figure the maximum weights are obtained for the criteria C51 (0.12027) followed by C52 (0.11752), C11 (0.09742), C45 (0.08965). Other considered criteria have moderate weight factors and the least weight factor is found in the criteria C13 (0.01292). By using these weights, the ranking of the alternatives is decided.

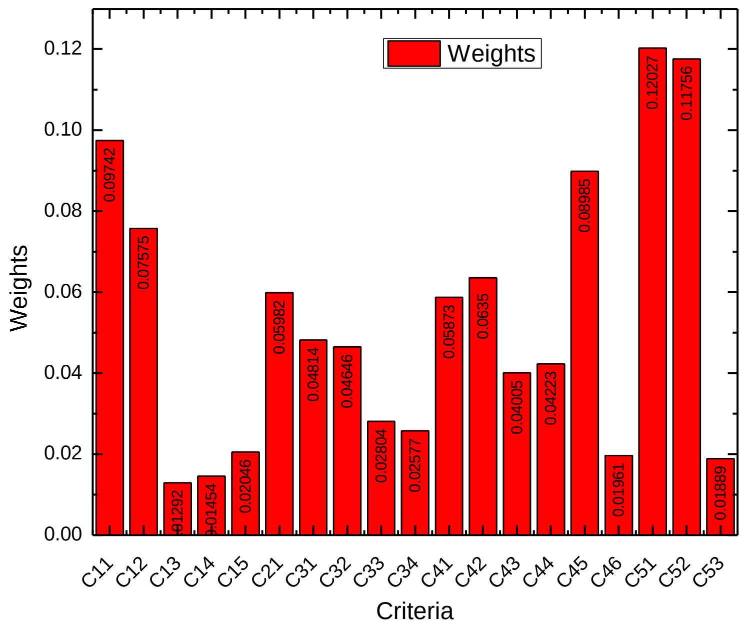


Fig. 4.7: Weights of the criteria

4.3.3.2 Ranking of alternatives:

The calculated weights help to decide the rank of the alternatives through the HFL-TOPSIS method. The evaluation criteria value for each alternative is converted into linguistic variables and it is shown in Table 4.13. The corresponding fuzzy numbers of these linguistic variables are discussed in Table 4.14. The analysis result is shown in Table 4.15.

Table 4.13: Linguistic term set for ranking analysis

Alternatives	C11	C12	C13	C14	C15	C21	C31	C32	C33	C34	C41	C42	C43	C44	C45	C46	C51	C52	C53
A1	F	F	HU	HS	HU	HU	S	F	HU	HS	HS	U	F	HS	F	S	S	F	HS
A2	HS	S	S	U	U	F	F	HS	F	F	HS	HS	S	U	F	S	U	U	HS
A3	S	HS	S	F	F	F	F	HS	F	S	S	S	HS	F	S	HS	S	HS	S
A4	S	F	U	S	S	S	U	S	S	U	F	HU	F	F	HS	F	U	HS	S
A5	S	HS	F	F	HS	S	U	S	HS	U	U	HS	F	HS	U	HS	HS	F	F
A6	U	F	F	U	S	S	HU	HU	U	HU	HS	F	U	HU	U	F	HS	S	HS
A7	U	F	U	F	F	HS	U	U	F	U	S	HU	S	U	HS	F	HS	S	S
A8	F	F	HU	S	U	U	HS	F	U	HS	U	U	S	HS	F	F	S	HS	F
A9	F	S	U	S	HS	S	U	S	HS	U	HS	HS	HS	F	U	F	F	F	F

Table 4.14: Fuzzy number of the alternative data

Alternatives	C11	C12	C13	C14	C15	C21	C31	C32	C33	C34	C41	C42	C43	C44	C45	C46	C51	C52	C53
A1	(3,5,7)	(3,5,7)	(1,1,3)	(7,9,9)	(1,1,3)	(1,1,3)	(5,7,9)	(3,5,7)	(1,1,3)	(7,9,9)	(7,9,9)	(1,3,5)	(3,5,7)	(7,9,9)	(3,5,7)	(5,7,9)	(5,7,9)	(3,5,7)	(7,9,9)
A2	(7,9,9)	(5,7,9)	(5,7,9)	(1,3,5)	(1,3,5)	(3,5,7)	(3,5,7)	(7,9,9)	(3,5,7)	(3,5,7)	(7,9,9)	(7,9,9)	(5,7,9)	(1,3,5)	(3,5,7)	(5,7,9)	(1,3,5)	(1,3,5)	(7,9,9)
A3	(5,7,9)	(7,9,9)	(5,7,9)	(3,5,7)	(3,5,7)	(3,5,7)	(3,5,7)	(7,9,9)	(3,5,7)	(5,7,9)	(5,7,9)	(5,7,9)	(7,9,9)	(3,5,7)	(5,7,9)	(7,9,9)	(5,7,9)	(7,9,9)	(5,7,9)
A4	(5,7,9)	(3,5,7)	(1,3,5)	(5,7,9)	(5,7,9)	(5,7,9)	(1,3,5)	(5,7,9)	(5,7,9)	(1,3,5)	(3,5,7)	(1,1,3)	(3,5,7)	(3,5,7)	(7,9,9)	(3,5,7)	(1,3,5)	(7,9,9)	(5,7,9)
A5	(5,7,9)	(7,9,9)	(3,5,7)	(3,5,7)	(7,9,9)	(5,7,9)	(1,3,5)	(5,7,9)	(7,9,9)	(1,3,5)	(1,3,5)	(7,9,9)	(3,5,7)	(7,9,9)	(1,3,5)	(7,9,9)	(7,9,9)	(3,5,7)	(3,5,7)
A6	(1,3,5)	(3,5,7)	(3,5,7)	(1,3,5)	(5,7,9)	(5,7,9)	(1,1,3)	(1,1,3)	(1,3,5)	(1,1,3)	(7,9,9)	(3,5,7)	(1,3,5)	(1,1,3)	(1,3,5)	(3,5,7)	(7,9,9)	(5,7,9)	(7,9,9)
A7	(1,3,5)	(3,5,7)	(1,3,5)	(3,5,7)	(3,5,7)	(7,9,9)	(1,3,5)	(1,3,5)	(3,5,7)	(1,3,5)	(5,7,9)	(1,1,3)	(5,7,9)	(1,3,5)	(7,9,9)	(3,5,7)	(7,9,9)	(5,7,9)	(5,7,9)
A8	(3,5,7)	(3,5,7)	(1,1,3)	(5,7,9)	(1,3,5)	(1,3,5)	(7,9,9)	(3,5,7)	(1,3,5)	(7,9,9)	(1,3,5)	(1,3,5)	(5,7,9)	(7,9,9)	(3,5,7)	(3,5,7)	(5,7,9)	(7,9,9)	(3,5,7)
A9	(3,5,7)	(5,7,9)	(1,3,5)	(5,7,9)	(7,9,9)	(5,7,9)	(1,3,5)	(5,7,9)	(7,9,9)	(1,3,5)	(7,9,9)	(7,9,9)	(7,9,9)	(3,5,7)	(1,3,5)	(3,5,7)	(3,5,7)	(3,5,7)	(3,5,7)

Table 4.15: Closeness coefficient and alternative's ranking:

Alternative	Closeness coefficients:	Rank
A1	0.0184	5
A2	0.0211	2
A3	0.0239	1
A4	0.0208	3
A5	0.0175	7
A6	0.0185	4
A7	0.0143	9
A8	0.0163	8
A9	0.0177	6

The HFL-TOPSIS analysis result shows that the location A3 is the best feasible location followed by A2, A4, and A6 for developing solar-wind based hybrid energy systems. The ranking of the locations A1 is 5, A9 is 6, A5 is 7 and A8 is 8. The first four rankings of the locations are similar to the result obtained through the NEAT-Fuzzy-PROMETHEE method. The next four rankings vary from the previous solutions. The least feasible location is A7 and it is similar to the previous analysis. Therefore both the analyses validate that the obtained result is robust and consistent. The proposed methodology decides that location A3 (Sailana) which is located at the western side of Madhya Pradesh is the best feasible solution to build the decentralized solar-wind based hybrid energy system. to meet the local energy demand. According to the study the considered factors are moderate for this location.

4.4 Summary of the chapter:

An integrated framework of methodology is proposed in this study to determine an optimal location for developing decentralized solar-wind-based HES. The study is performed for Madhya Pradesh, a central state of India. The overall analysis result shows that the most feasible location is A3 (i.e., Sailana) followed by A2 (Bhanpura), A4 (Bhind), A6 (Lanji). The least feasible location is A7 (Dindori). The optimal site is located at the western part of the state and the least feasible site is situated in the eastern region of the state. According to the quantitative criteria data the optimal location receives a good solar irradiation (5.31 kWh/m2/day) with an available wind speed (5.54 m/s). The other important factors such as elevation, aspect, slope, temperature are moderate for this location. This area is mainly grass land which is also suitable for developing the projects. The location is nearer to the rural area (4.77 km) and moderately distant from the urban area (i.e., 12.79 km). The distance of protected areas and water bodies are also suitable for this location. Thus, this location is practically most suitable among the considered alternatives in this state for developing decentralized renewable HES. The sensitivity analysis also validates that the obtained solution is quite robust.

Chapter-5

Techno-Economic optimization of decentralized HESs*

(***Das, S.**, Ray, A., De, S.* (2020): Optimum combination of renewable resources to meet local power demand in distributed generation: A case study for a remote place of India. **Energy (Elsevier)** (**Published**). DOI: https://doi.org/10.1016/j.energy.2020.118473)

5.1 Objective of the work:

This study explores techno-economic optimization with least carbon-emission energy solution for a remote hilly village of the northeastern state of Arunachal Pradesh, India. National grid power is not suitable here due to adverse terrain conditions in this location. Three locally available primary renewable resources, solar, wind, and hydro are optimally hybridized for economic and environmental indicators to meet the load demand of the village. HOMER® and MCDM approaches are used to find the best feasible hybrid combination. The TOPSIS-MCDM method is used to decide the rank on the basis of techno-economic and greenhouse gases (GHG) optimization results provided by the HOMER®.

5.2 Study area details:

The proposed hybrid renewable energy solution is explored for a remote hilly village of the northeast state of Arunachal Pradesh, India. Arunachal Pradesh placed between 27.08˚ to 28.21˚ N and 93.40˚ to 94.72˚ E (Balasubramanian, 2017). The Singa old village (latitude and longitude are 28.8 ˚N and 95.14˚ E respectively) is located in the upper Siang district of Arunachal Pradesh under Singa Tehsil. This study area is located at 40 km away from the sub-district headquarter Singa and 280 km away from the district headquarter, Yingkiong (Balasubramanian, 2017). The total population of the study area is 40 living in ten households (Chandramouli, 2011). Fig. 5.1.a shows the location of the state of Arunachal Pradesh in the Indian map. Figure 5.1.b shows the study location (Singa old village) with its surrounding topography. Fig. 5.1.c represents households of that village (Planemad, 2006).

(a)

(b) (c)

Fig 5.1. (a): Geographical location of Arunachal Pradesh. (b): Location of the Singa Old village, Arunachal Pradesh (c) A typical photo of the Singa old village (Planemad, 2006)

5.3 Materials and methods:

Solar, wind, and hydro resources are identified as available renewable resources for power generation in this study area. A battery is also integrated to accommodate the intermittency of these renewable resources. Finally, when a solar-wind-hydro system supported by the battery fails to meet the local load demand, a diesel generator set (DG set) will start operating to meet the additional demand for the required period only. Possible combinations of different energy resources are explored to determine the optimum combination through the HOMER® and MCDM approach.

5.3.1 Inputs for hybrid system modelling:

The necessary inputs for designing hybrid systems with the governing equations of the components used in this analysis are described as follows:

5.3.1.1 PV module modelling:

The output power of the PV module is discussed in equations shown in Table A. 1, Sl. No.: 1, Eqs. i-iii (Babatunde et al., 2022; Emad et al., 2021; Mandal et al., 2018) in Supplementary Index (SI).

In this study, polycrystalline Canadian solar PV modules are used. This is mainly incorporated with 60 polycrystalline cells and model number CS6P-250P. This PV module is suitable in this lower range of solar energy, and also the installation cost is lesser than other PV modules (Nag & Sarkar, 2018). The detailed specification is provided in Table 5.1.

5.3.1.2 Wind turbine modelling:

The output power of the wind module is discussed in equations shown in Table A. 1, Sl. No.: 2, Eqs. i-iii (Emad et al., 2021) in SI.

The hub height of the wind turbine is kept approximately 10m or above for a search space of 0-5 kW. The other specifications are provided in Table 5.1 (Nag & Sarkar, 2018).

5.3.1.3 Hydro turbine modelling:

The output power of the hydro module is discussed in the equation shown in Table A. 1, Sl. No.: 3, Eq. i (Arévalo et al., 2020) in SI. Detailed specifications are provided in Table 5.1 (Muh & Tabet, 2019; Nag & Sarkar, 2018; Office of Energy Efficiency and Renewable Energy, 2019).

5.3.1.4 Storage system:

The equations of storage systems are discussed in Table A. 1, Sl. No.: 4, Eqs. i-v in SI (Baneshi & Hadianfard, 2016).

In this analysis, 1kWh li-ion battery is considered (www.cdtechno.com/product/lithium, 2019). It is highly efficient. It has a longer lifespan and gets charged faster. The capital, O&M costs are lesser than other battery modules (Ciupageanu & Lazaroiu, 2018; Relion, 2019). The techno-economic parameters of this storage system are shown in Table 5.1.

5.3.1.5 Converter system:

The equation of the converter system is discussed in Table A. 1, Sl. No.: 6, Eq. i in SI (Emad et al., 2021).

In this analysis, a 1kW parallel-connected boost converter system is attached to convert DC-AC (www.enfsolar.com/pv/inverter-datasheet, 2019). The detailed specifications of the converters are shown in Table 5.1 (Geetha et al., 2016).

5.3.1.6 Diesel generator (DG) modelling:

The equation of DG system is discussed in Table A. 1, Sl. No.: 5, Eq. i in SI (Ramesh & Saini, 2020).

In this study, the lowest capacity diesel generator (10kW/12.5kVA fixed capacity power generator (kohlerpower.com, 2019)) available in the market is used. The detailed specifications of these system components are discussed in Table 5.1. The overall conceptual schematic diagram of the hybrid energy system is shown in Fig. 5.2.

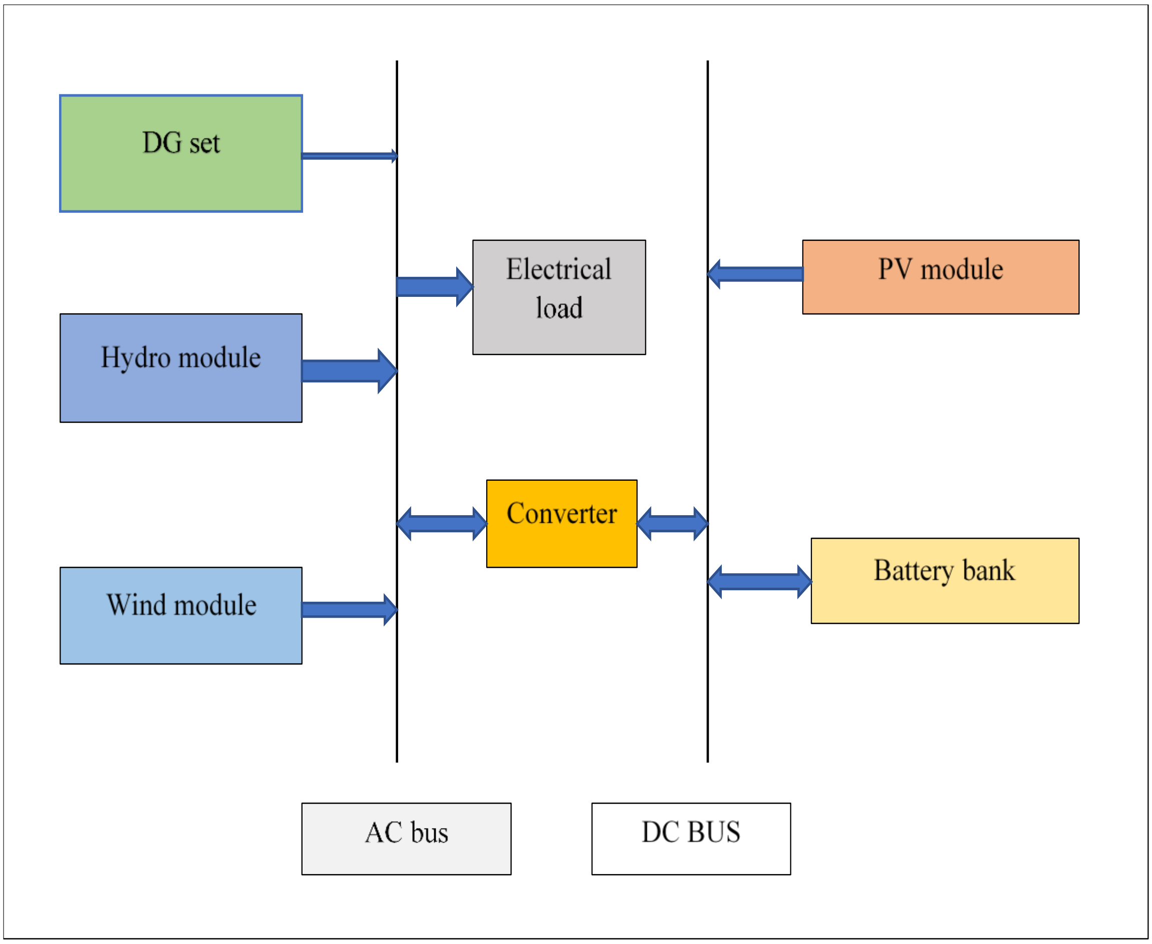


Fig 5.2: Schematic diagram of the hybrid system

Table 5.1: Detailed specifications of components: (Muh & Tabet, 2019; Nag & Sarkar, 2018; Office of Energy Efficiency and Renewable Energy, 2019; Ciupageanu & Lazaroiu, 2018; Relion, 2019; Geetha et al., 2016; kohlerpower.com, 2019)

PV module		**Wind Turbine**		**Hydro turbine**		**Converter**		**Diesel generator**		**Battery**	
Parameters	Specifications	Parameters	Specifications	Parameters	Specifications	Parameters	Specifications	Parameters	Specifications	Parameters	Specifications
Efficiency	80%	Efficiency	80-85%	Available head	10 m	Efficiency	95%	Load ratio	25%	Efficiency	90%
MPPT	0	Hub height	10 m	Design flow rate	179.25 m/s	Load meeting	10%	Lifetime	15000 h	Lifetime	20 years
Azimuthal angle	0	Temp dependence	0	Max flow rate	50 m/s	Lifetime	15 years	Fuel curve intercept	0.480l/h	Throughput	3,000.00 kWh
Derating factor	0.7-0.8	Rated Power	500 W	Min flow rate	200 m/s	Relative capacity	10%	Fuel curve slope	0.286 l/h/kw	N.V.	6V
Reflectance	20-70%	Rated Voltage	24/12 V	Efficiency	70 %	Capital Cost	$409/kW	L.H.V.	43.2 MJ/kg	M.C.C	167 A
Nominal max. Power	250W	Cut-in Speed	4.02	Nominal Capacity	12.3 kW	O&M		Density	820 kg/m^3	Capital Cost	$80/kW
Optimum operating voltage	30.1 V	No. of Blades	3	Pipe head loss	15 %	Replacement cost	$409/kW	C & S amount	88%, 0.4%	O&M	$8/kW/year
Optimum operating current	8.3 A	Capital Cost	$1200/kW	Capital Cost	$1000/kW			Capital Cost	$409/kW	Replacement cost	$80/kW
V_{OC}	37.2 V	O&M	$18/kW/year	O&M	$44/kW/year			O&M	$0.3/kW/year		
I_{SC}	8.87 A	Replacement cost	$1200/kW	Replacement cost	$500/kW			Replacement cost	$409/kW		
Capital Cost	$1667/kW	Lifespan	15 years								
O&M	$19.38 /kW/year										
Replacement cost	$1667/kW										
Lifespan	20 years										

5.3.2 Energy resource and load data:

5.3.2.1 Solar energy data:

The monthly average solar radiation data for Arunachal Pradesh is obtained from the National Renewable Energy Laboratory (NREL) and is used as input to this study (NREL, 2019). The input data is shown in Fig. 5.3. The solar clearness index is calculated by using Eq. 5.1 (Akikur et al., 2013):

$$K_T = \frac{H_{ave}}{H_{0,ave}} \tag{5.1}$$

K_T is the clearness index (monthly basis), H_{ave} is the monthly average radiation on a horizontal surface in kWh/m^2/day, $H_{0,\ ave}$ is the extra-terrestrial horizontal radiation. According to Fig. 5.3, it is observed that the solar radiation throughout the year is between 2.23-6.53 kWh/m^2/day. The monthly average solar radiation is 3.84 kWh/m^2/day (NREL, 2019).

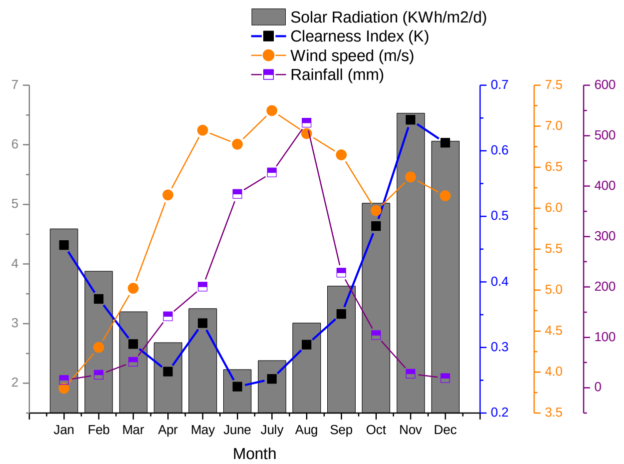


Fig. 5.3: Resources data (NREL, 2019)

5.3.2.2 Wind energy data:

The wind energy data of this area is collected from the NREL meteorology system (NREL, 2019). The monthly wind speed varies between 4-7 m/s with an average of 6.02 m/s for this region. Due to the higher average wind speed, the cut in and cut off speed of the turbine are considered as 4.02-6.89 m/s (Www.Worldweatheronline.Com/Arunachal-Pradesh-Weather, 2019). The wind speed variation is shown in Fig. 5.3.

5.3.2.3 Hydro energy data:

For this hybrid energy system, another available energy resource is hydro energy. Local rainfall is the source of this small hydropower. The average monthly rainfall data is collected from the NREL meteorological site (NREL, 2019). Graphical representation of this rainfall data is shown in Fig. 5.3.

5.3.2.4 Electrical load estimation:

In this study, the projected load is calculated with known households for the residential area of the Singa old village in Arunachal Pradesh (Balasubramanian, 2017). The load data is shown in Fig. 5.4. During summer, the average load is 11.13 kWh/day with a peak load of 2.09 kW. During winter this is 10.65 kWh/day with a peak load of 1.95 kW (Chandramouli, 2011). Over the year, the average load is 10.89 kWh/day with a peak load of 2.02 kW.

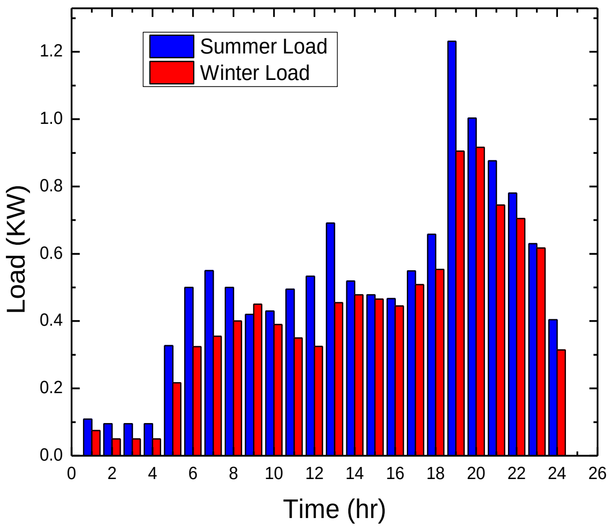


Fig 5.4: Load profile (Balasubramanian, 2017; Chandramouli, 2011)

5.3.3 System methodology:

The hybrid energy system options are simulated and optimized with HOMER®. The HOMER® minimized the economic parameters such as cost of electricity (COE), net present cost (NPC), and O&M cost of the model based on the provided inputs. By using these output parameters, the MCDM analysis is done. The TOPSIS algorithm method is used as the MCDM approach. The MCDM analysis provided the best feasible renewable energy option that satisfied the objective function. The flowchart of the methodology of this analysis is shown in Fig. 5.5.

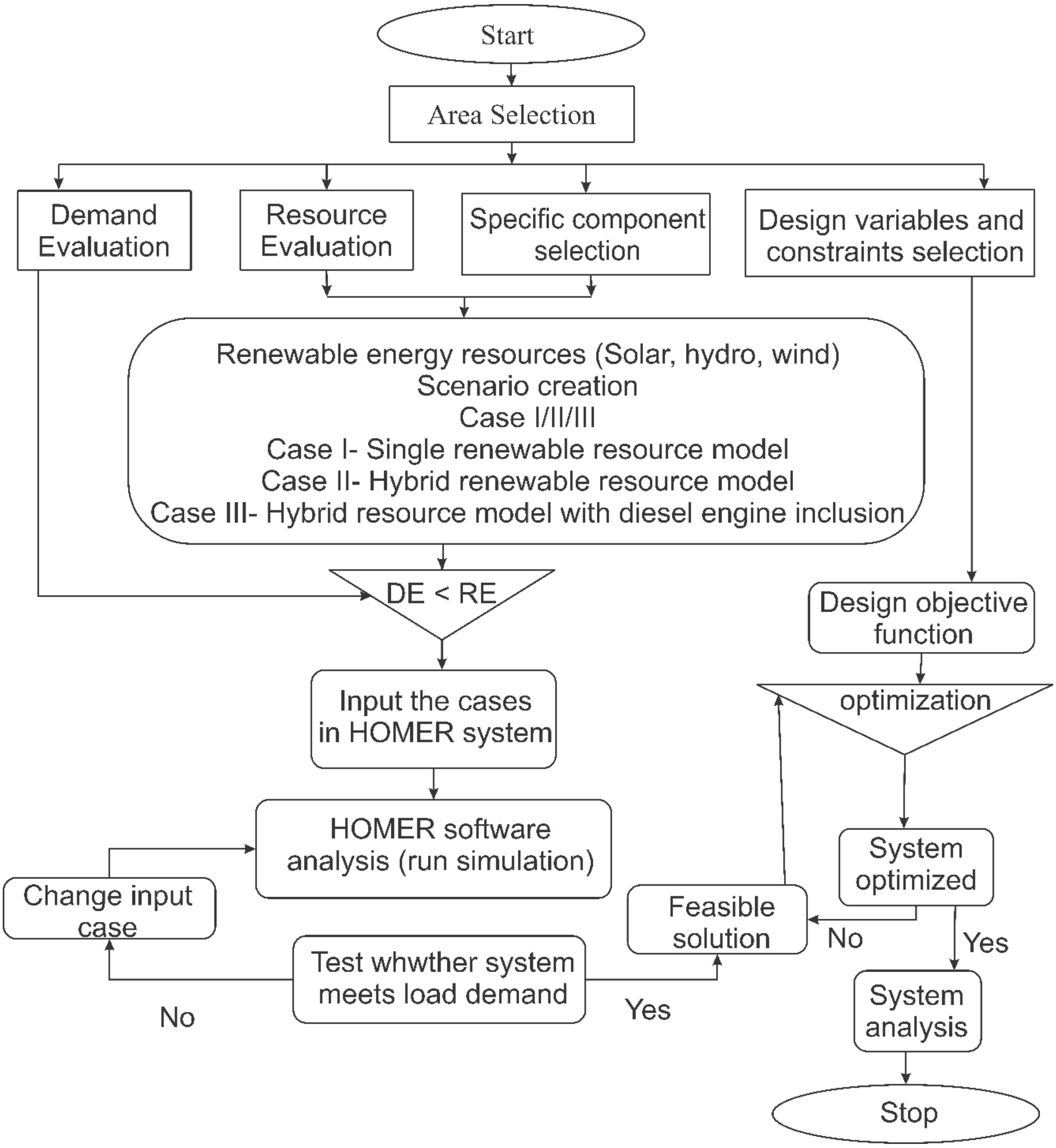


Fig. 5.5: Flowchart of the detailed methodology

5.3.3.1 HOMER® methodology:

The HOMER® is used to analyze the systems' techno-economic feasibility, sensitivity, and optimization of hybrid energy systems. This was designed by the National Renewable Energy Laboratory (NREL), United States. Techno-economic parameters of components, resource data, electrical load data, and others are used as inputs for the HOMER® (Li et al., 2020). From this simulation, the feasible optimum solution is obtained based on simultaneous economic and environmental performance. The working principle of HOMER® is shown in Fig. 5.6.

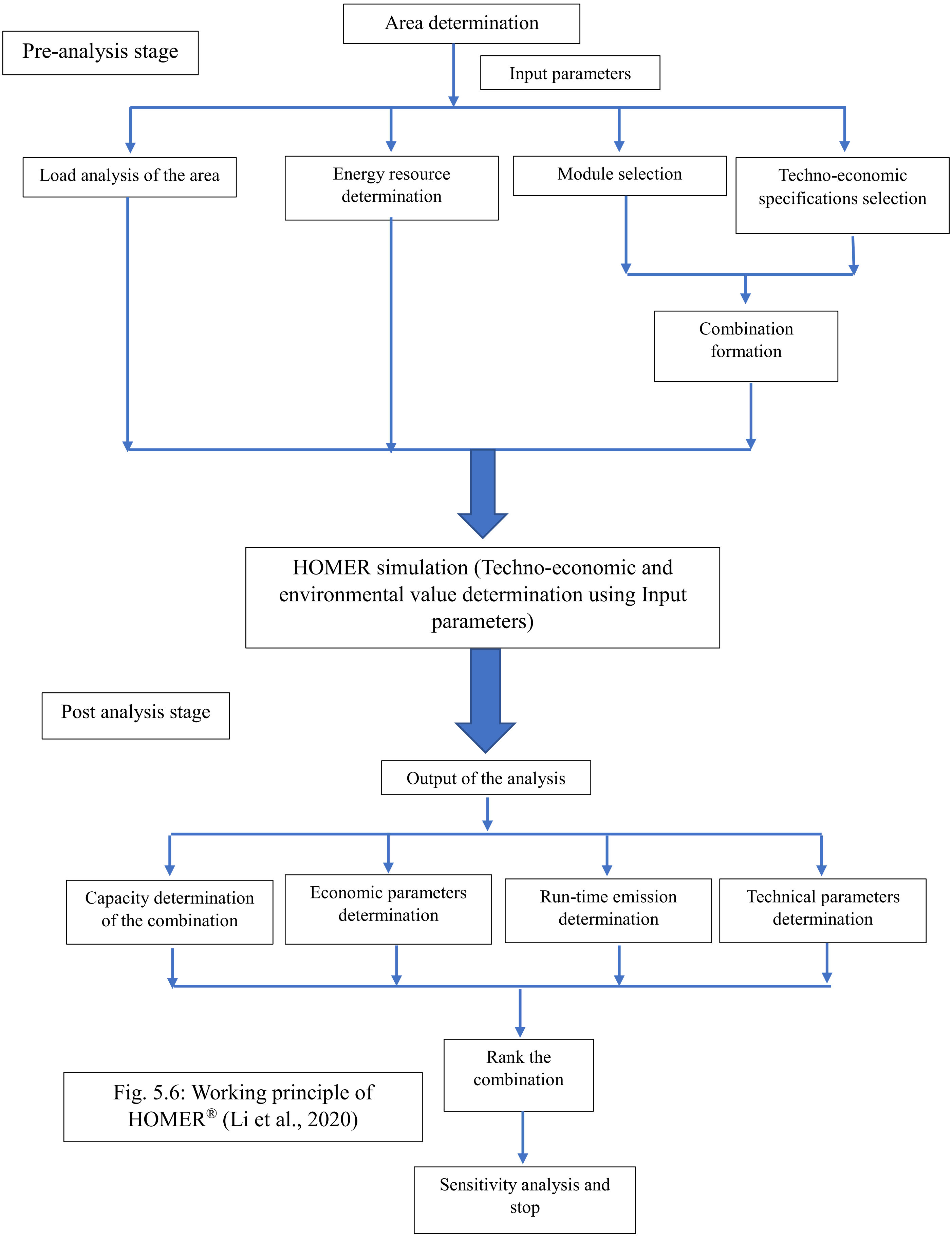


Fig. 5.6: Working principle of HOMER® (Li et al., 2020)

5.3.3.2 MCDM approach:

The multi-criteria-decision-making (MCDM) approach is used to decide the optimum feasible solution based on MCDM attributes (Lozano-Minguez et al., 2011). The TOPSIS-MCDM method is used in this study.

5.3.3.2.1 TOPSIS-MCDM algorithm:

The 'Technique for Order of Preference by Similarity to the Ideal Solution' (TOPSIS) is a multi-criteria decision-making approach. According to the TOPSIS algorithm, the best solution should have the shortest distance from the positive ideal solution and the longest distance from the negative ideal solution (Diemuodeke et al., 2016). The steps followed by the TOPSIS-MCDM method are shown in Fig. 5.7.

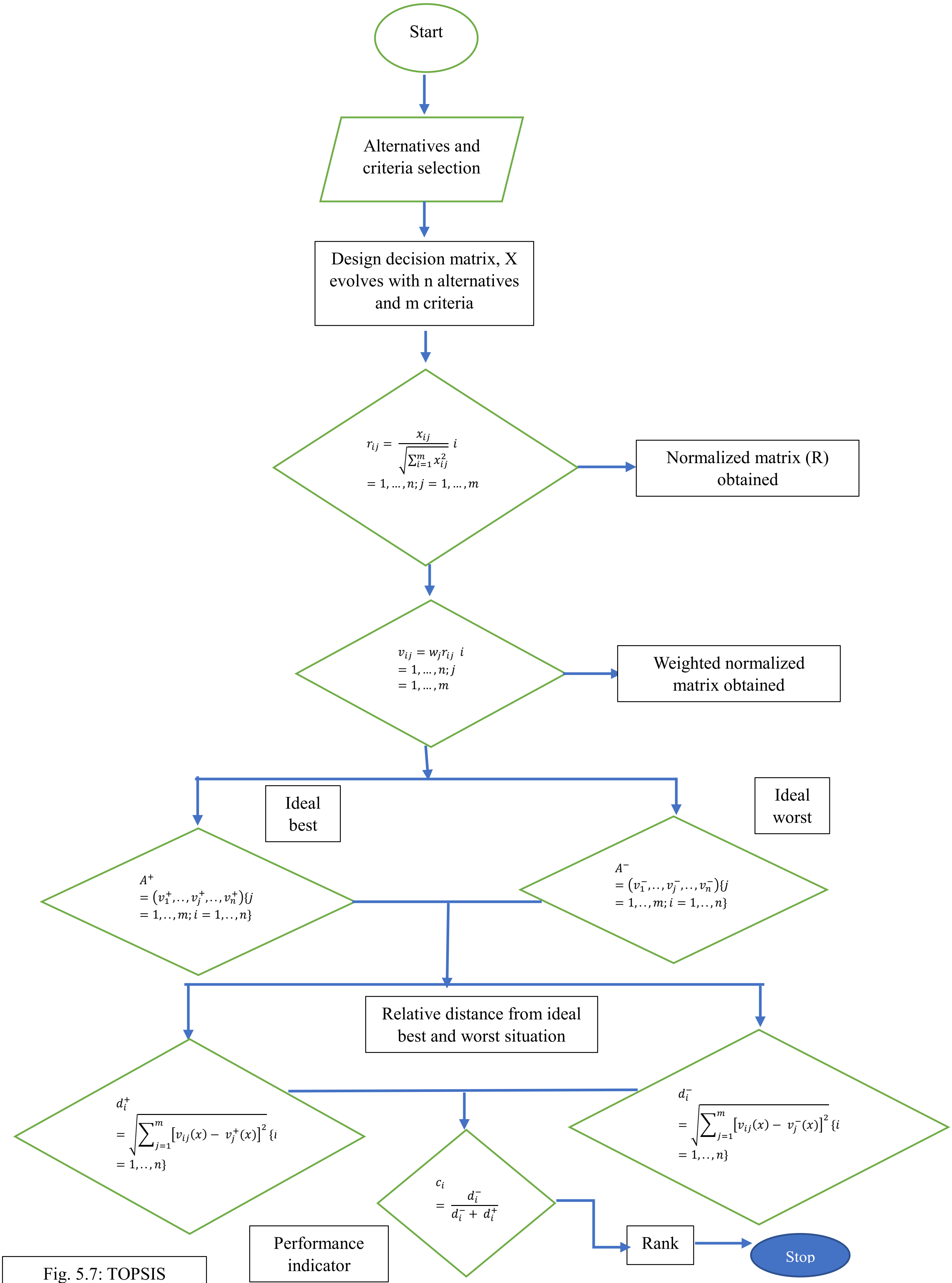


Fig. 5.7: TOPSIS approach (Diemuodeke et al., 2016)

5.3.4 MCDM attributes:

The main attributes for the decision-making approach are technical, economic, and environmental. In this study, COE, NPC, O&M, and renewable fraction (RF) are considered as attributes.

5.3.4.1 Economic analysis:

The economic model is simultaneously assessed with the systems' performance analysis to judge the overall feasibility of the hybrid model (Khalid et al., 2017; Khan et al., 2021). Several economic parameters like COE, NPC, and O&M costs are discussed in this section.

5.3.4.1.1 Operational and Maintenance (O&M) cost:

The O&M cost is shown in Eq. i, in Table A.2, Sec. 2.iv of SI.

The penalty cost for the capacity shortage and the carbon emission penalty costs are shown in Eqs. i-ii, Sec. 2.v in Table A.2 of SI.

Penalty cost for carbon emission is only considered as the other emitted gases are negligible. The penalty for carbon emission is \$10/ton in India (Ernst & Young LLP, 2018).

5.3.4.1.2 Cost of electricity (COE):

The COE is shown in Eq. i, in Table A.2, Sec. 2.ii of SI.

For this study fuel cost is also needed to include because the use of a diesel generator is necessary to meet the load in the area.

5.3.4.1.3 Net Present Cost (NPC):

The NPC is shown in Eqs. i-iii, in Table A.2, Sec. 2.i of SI.

5.3.4.1.4 Renewable Fraction (RF):

The RF is shown in Eq. i, in Table A.2, Sec. 3.i of SI.

5.3.5 Design variables and constraints:

The equation of the objective function included the design variables, i.e., COE, NPC and O&M cost of the system. In this study, a few constraints are considered which is shown in Table 5.2. The lifetime of the system, the penalty cost for the carbon emission and the minimum renewable penetrations are the constraints of optimization (Sen & Bhattacharyya, 2014).

5.3.5.1 Objective functions:

Based on the design variables and constraints, a global objective function is defined. The goal of optimization is to determine the most economic combination of locally available energy resources to meet the power demand of the test site. The objective function is defined in Eq. 5.9 and adopted from ref. (Ma et al., 2018)

$$Function = \min(\sum_{i=1}^{I} CI.N_C + \sum_{i=1}^{I}\sum_{j=1}^{J} C_{O\&M}.N_c + \sum_{i=1}^{I}\sum_{j=1}^{J} C_r.N_c + \sum_{i=1}^{I}\sum_{j=1}^{J} C_{diesel}.N_c \quad (5.9)$$

Where, CI is the capital investment, $C_{O\&M}$ is the operation and maintenance cost, C_r is the replacement cost, C_{diesel} is the cost of the diesel used in the DG set. Units of all the cost items are in \$. N_c is the component capacity in kW.

5.3.6 Sensitivity analysis:

The sensitivity analysis of any energy model is necessary to evaluate the vulnerability of the performance of the modeled energy system with varying parameters (Jana et al., 2017). Variations of COE and NPC of the energy system with varying input parameters indicate the system's economic reliability. Input parameters considered for the sensitivity analysis are hydro flow rate, discount rate, and wind speed. The ranges of values of these input parameters are shown in Table 5.3.

Table 5.2: Design constraints (Sen & Bhattacharyya, 2014)

Constraints	Specifications
Project lifetime	25 years
Min. renewable penetration	55%
Penalty cost for carbon emission	$10/ton

Table 5.3: Parameters with values/range of values for sensitivity analysis (Jana et al., 2017)

Sensitivity analysis parameters	Specifications
Hydro flow rate	150-220 l/s
Discount rate	10%,12%,14%,16%
Wind speed	4-7 m/s

5.4 Results and Discussions:

In this study, renewable energy with battery storage backup is evaluated to find a suitable option that could meet the local load demand by simultaneously minimizing the cost parameters (COE, NPC, and O&M) and GHG emissions.

5.4.1 Single resource model performance analysis:

At the first phase of this analysis, the possibility of meeting the load by using any one renewable resource only at a time of all three available, i.e., solar, wind, and small hydro is assessed. Each of these single resource models also includes the battery storage backup to accommodate the load fluctuations. Four parameters are used to examine the sustainability of these options. These parameters are COE, NPC, O&M, and average unmet load (UL). The performance of single resource options, represented by values of these four index parameters are as shown in Fig. 5.8.

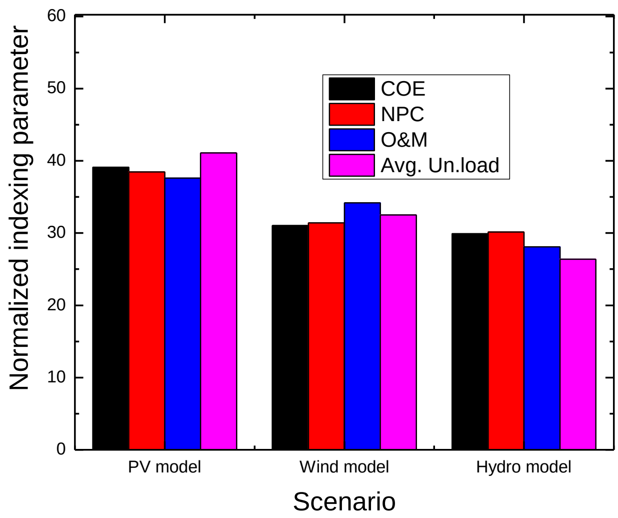


Fig. 5.8: Performance analysis summary of the single resource models

According to Fig 5.8, each single resource option with the battery backup has high values of COE, NPC, and O&M. The analysis result shows that the normalized values of COE and UL for these three scenarios are high and approximately in the range of 30-40. Intermittency of renewable resources is the reason for such high values of index parameters, specifically the COE and the UL. According to this analysis, no single resource with battery backup can meet the load demand of the area (i.e., with significant UL) both during winter and summer. Due to the high values of COE and UL, these options are neither economic nor enough to meet the load demand alone. Hence, the hybridization of more than one renewable resource is then explored.

5.4.2 Hybrid renewable model performance analysis:

In the second step of the analysis, at least two of the renewable resources are considered for the hybridization to meet the local load. Next, it is extended to include all three renewable resources together. For all these studies battery storage backup is included to accommodate instantaneous fluctuations of both renewable resources and load demand over the day. The hybridization of different renewable resources would not only increase the capacity but would also complement the intermittency. In this process, four maximum possible hybrid scenarios evolve which can meet the load demand both during winter and summer by simultaneously minimizing the corresponding cost parameters. The result of this analysis is shown in Fig.5.9.

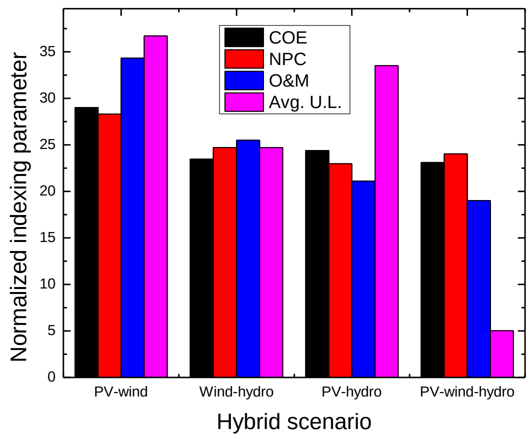


Fig. 5.9: Performance analysis summary of the hybrid resource models

As observed from Fig. 5.9, the amount of UL from all four hybrid options considered in this analysis is lesser than each of those for previous single resource options. The best option with minimum UL and costs is obtained for the PV-wind-hydro combination rather than combining any two of these three. Also, the UL for the combination of all three happens only during winter due to the very little availability of water flow in springs, i.e., small hydro resources. According to the figure the parameters for different costs are also relatively high for each of these hybrid scenarios.

Combinations achieved in the previous two cases are the most suitable options though these simulated models are falling short to meet the load demand fully. In the next step, the hybrid models are combined with the required minimum capacity of the diesel generator to meet the local load demand. Any other energy supply option is not viable at this remote site due to cost constraints. Increasing the capacity of other components (say, battery, wind turbine, etc.) to meet occasional peak loads will increase the COE of the system significantly. Adding DG set with the hybrid renewable combination is considered as the best possible option to meet the full demand with minimum COE.

5.4.3 Hybrid resource with diesel generator model performance analysis:

The inclusion of the DG with the hybrid renewables and battery can meet the full load demand including occasional peaks during both summer and winter. With options of meeting the full load, economic (COE, NPC, and O&M) and emission are minimized next. The economic parameters like COE, NPC, and O&M and environmental parameters such as RF and GHG emission along with the reserved capacity of the hybrid renewable energy system with diesel generator are shown in Table 5.4.

Table 5.4: Hybrid models analysis data with the inclusion of the DG set

Scenario/Combinations	COE ($/kWh)	NPC ($)	O&M ($/year)	Reserved Capacity (kWh/year)	RF (%)	GHG emission (Kg/year)
PV-Wind-Generator-Battery	0.87	27456	1091.25	2359	51.2	1056
Wind-Hydro-Generator-Battery	0.63	23808	806.3	4184	88.1	481
PV-Hydro-Generator-Battery	0.71	25698	948.32	3268	74.1	625
PV-Wind-Hydro-Generator-Battery	0.68	24158	831.24	4589	89.5	318

According to the table PV-wind-hydro-generator-battery combination has the highest reserved capacity (4589 kWh/year), the maximum renewable fraction (i.e., RF= 89.5%), and lowest GHG emission (318kg/year). So, with respect to the reserved capacity, GHG emission, and RF, the PV-wind-hydro-generator-battery system offers the best performance as shown in Table 5.5. However, this option is not the best with respect to economic parameters (COE, NPC, and O&M cost). Wind-hydro- generator-battery systems offer least COE, NPC, and O&M cost (approximately $0.63/kWh, $23808, and $806.3/year respectively). The renewable fraction is less and the carbon emission is more than those of PV-wind-hydro-generator-battery systems out of all available options. As all parameters are not showing the best performance for any single combination it needs further analysis to get the best option.

Multi-criteria decision-making (MCDM) approach is applied for further analysis. Attributes are to be decided for MCDM. Major constraints are considered as attributes for the decision process. COE, NPC, O&M, and RF are decided as major attributes based on which the best possible option is decided. Table 5.5 shows the values of the attributes of these four alternatives. Based on these alternatives and using the TOPSIS algorithm, the MCDM approach is processed. The results of this analysis are shown in Table 5.6. Table 5.6 shows the relative closeness of the scenario is calculated by Eq. 5.8.

Table 5.5: Selected attributes for the MCDM approach/Initial decision matrix:

Scenario/Combinations	**Criteria**			
	COE	NPC	O&M	RF
PV-Wind-Generator	0.87	27456	1091.25	51.2
Wind-hydro-Generator-Battery	0.63	23808	806.3	88.1
PV-Hydro-Generator-Battery	0.71	25698	948.32	74.1
PV-Wind-Hydro-Generator-Battery	0.68	24158	831.24	89.5

Table 5.6: Relative distances with rank

Scenario	**Distance**		**Relative distance**		**Rank**
	S+	S-	S (+) +S (-)	P(i)	
PV-Wind-Generator	0.085	0	0.085	0	4
Wind-hydro-Generator-Battery	0.002	0.084	0.086	0.973	1
PV-Hydro-Generator-Battery	0.035	0.05	0.086	0.588	3
PV-Wind-Hydro-Generator-Battery	0.009	0.079	0.089	0.895	2

By applying the MCDM approach using the TOPSIS algorithm, the best feasible hybrid energy option that satisfies the local load demand is wind-hydro-generator-battery. The relative closeness of this scenario is 0.974 followed by the relative closeness of PV-wind-hydro-generator-battery which is approximately 0.895. In the third position, PV-hydro-generator-battery stands with the relative closeness of 0.588. The relative closeness of PV-wind-generator – battery is 0 and hence it proves to be the worst scenario. This PV-wind-generator-battery system has the lower renewable fraction and due to more use of diesel generators, this system has higher GHG emissions. This best feasible option, i.e., wind-hydro-generator-battery has a

COE of \$0.63/kWh, NPC of \$23808 with an RF of 88.1%. This best scenario is feasible for the study area to meet the load demand with the lowest economy and for moderate GHG emission.

Table 5.7 gives the individual components of the components for all the combinations analyzed in HOMER®. The technical details of these overall scenarios considered in this study are shown in this table.

Table 5.7: Optimum result from techno-economic analysis

Scenario/Combinations	**Individual capacity(kW) of the components of hybrid combinations**					
	PV (kW)	Wind (kW)	Hydro (kW)	Gen (kW)	Battery (kWh)	Converter (kW)
PV-Battery	0.712	-	-	-	29	1.97
Wind-Battery	-	3	-	-	23	1.79
Hydro-Battery	-	-	12.3	-	26	1.91
PV-Wind-Battery	0.605	2	-	-	21	1.81
Wind-Hydro-Battery	-	3	12.3	-	26	1.49
PV- Hydro-Battery	2.49	-	12.3	-	47	2.37
PV-Wind-Hydro-Battery	0.654	2	12.3	-	20	1.69
PV-Wind-Gen-battery	0.00108	2	-	10	12	1.84
Wind-Hydro-Gen-Battery	-	1	12.3	10	7	1.96
PV- Hydro- Gen-Battery	0.774	-	12.3	10	4	2.56
PV- Wind-Hydro-Gen-Battery	0.0110	1	12.3	10	6	2.01

5.4.4 Detailed analysis of the best feasible scenario:

5.4.4.1 Energy production analysis:

The month-wise share of electrical outputs from different sources for the best scenario is shown in Fig. 5.10 which illustrates the contribution of each of the component resources used in this scenario. According to this figure, the hydro resource is available in a sufficient amount for electricity generation during the rainy season (June-Oct.). It decreases during the winter (Nov-March). On the other hand, wind resources are more steadily available throughout the year. The diesel generator is used only during winter as an 'emergency storage device' to meet the peak load.

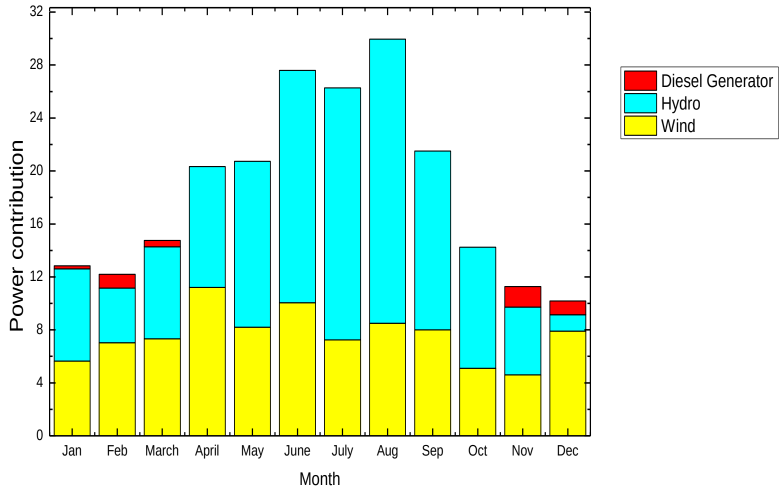
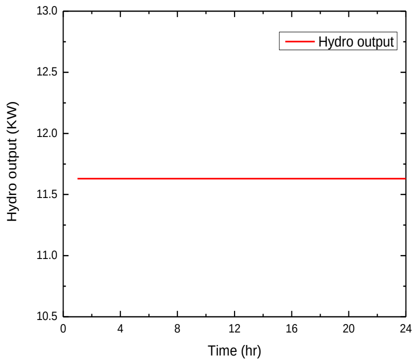
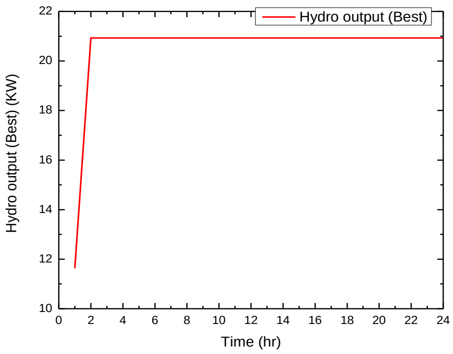


Fig. 5.10: Monthly shares of component wise power generation for the best combination

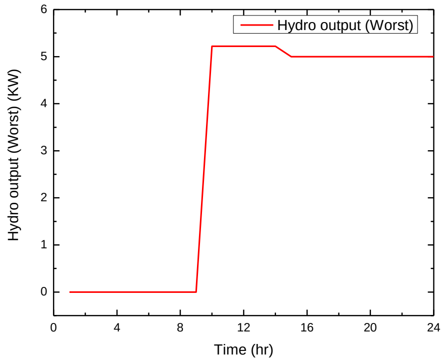
Figures 5.11.i (a, b and c) show hydropower output for a typical a) normal, b) best and c) worst day respectively. A similar figure for wind power is shown in Figs. 5.11. ii. Figure iii represents the DG set normal and working conditions. All these figures are taken when the hybrid system is in operating condition. It is noted from Figs. 5.11. i and ii that the power output from the hydro module is more uniform than that of the wind module. The DG set supplies power to the load only when hydro and wind modules together fail to meet the local load demand.



(a) Daily hydro power output (normal case)

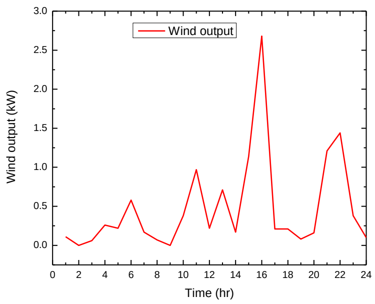


(b) Daily hydro power output (best case)

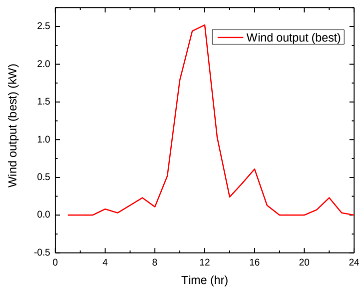


(c) Daily hydro power output (worst case)

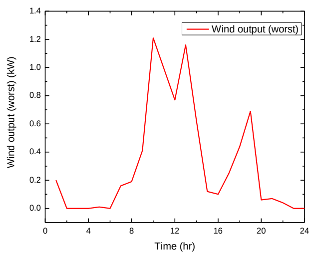
Fig. 5.11.i). (a), (b) & (c) Hydro power output fluctuations on daily basis (normal, best and worst case)



(a) Daily wind power output (normal case)

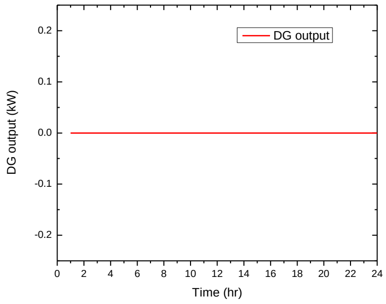


(b) Daily wind power output (best case)

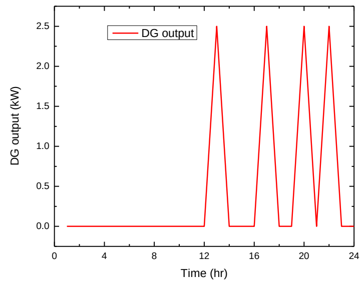


(c) Daily wind power output (worst case)

Fig. 5.11.ii). (a), (b) & (c) Wind power output fluctuations on daily basis (normal, best and worst case)



(a) Daily DG power output (normal case)



(b) Daily DG power output (working case)

Fig. 5.11.iii). (a), & (b) DG power output fluctuations on daily basis (normal, and working case)

5.4.4.2 Percentage of energy sharing:

The percentage distribution of electricity from different sources is shown in Fig. 5.12. This hybrid renewable system produces 78,000 kWh/year electricity which satisfies the yearly local load demand. 4,184 kWh/year electricity is considered as the reserved production which is stored in the battery for future use. Out of this total generation, 56.89% of energy is contributed by the hydro module. It contributes maximum share out of all sources of this hybrid energy system. Wind module contributes (41.17%) and diesel generator contribution is only 1.94%.

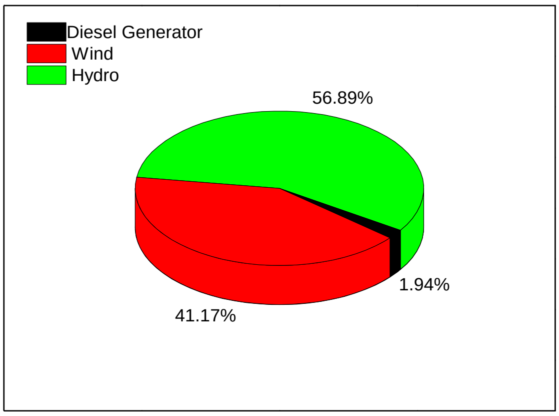


Fig. 5.12: Yearly share (%) of power generation from different sources for the best case

5.4.4.3 Detailed energy assessment of component modules:

The small hydro system contributes 44,374.2 kWh electricity per year. The rated capacity of the small hydro module is 20 kW, the mean output is 13.82 kW and the maximum output is 18.9 kW with a capacity factor of 69.4%. The hour of operation of this small hydro turbine is

5136 h/year. This module has a COE of \$0.238/kWh. Another important renewable component of this hybrid system is the wind energy module which delivers 32,112 kWh energy throughout the year in 7,176 hours of operation. The wind penetration in this system is approximately 10%. This module is 3 kW of rated capacity and produces the maximum output of 3kW and a mean output of 0.814 kW with a capacity factor of 22.2%. The COE is \$0.071/kWh. DG is not required during April to October since small hydro and wind outputs together are sufficient to meet the load demand. Only, during the winter period, the DG becomes essential to manage occasional peak loads and the total working hours of the DG is 654 h/year. The capacity factor of the DG is 0.439% and it generates approximately 1513 kWh per year. The mean electrical output is 2.5kW. A penalty cost of CO_2 emission from the DG is assigned as an O&M cost to decide the optimal solution out of available options.

5.4.4.4 Cost analysis of the best scenario:

In the present study, COE, and NPC are considered as the two main indicators for the assessment of the economic performance of the energy system. Variations of COE and NPC with variations of different design and operating parameters are studied to access the sensitivity and long-term feasibility of the system.

5.4.4.4.1 COE analysis:

The average COE of the hybrid system is estimated as \$0.63/kWh. DG has the maximum contribution of \$0.301/kWh to this COE. This includes the penalty cost for CO_2 emission from the DG also. The contribution of the hydro module is \$0.238 /kWh and those of the wind module and the battery unit are (\$0.071/kWh) and (\$0.091/kWh) respectively.

5.4.4.4.2 NPC and O&M cost analysis:

Another parameter of the cost analysis of this system is NPC as it is necessary to analyze the NPC distribution for improving the economic performance of the system. The total NPC of the best option is \$23,808 and the O&M cost of the system is \$806.30/year. Figure 5.13 summarizes the NPC share of each component. According to this figure, the highest share of NPC is due to the hydro module, i.e., 77.12% (\$18,332) followed by those of the wind module (9.25%), system converter (6.15%), battery (4.32%), and DG set (3.15%).

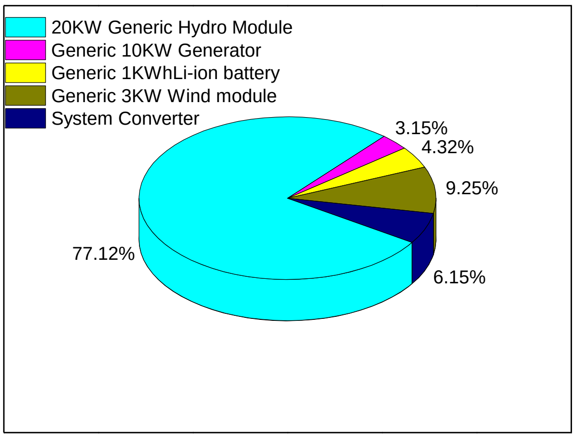


Fig. 5.13: Shares of NPC (%) of different component modules

5.4.4.4.3 Project lifetime and COE, NPC relation:

In Fig. 5.14 the variations of COE and NPC with a varying lifetime of the hybrid system are shown. As expected, both COE and NPC decrease with an increasing lifetime of the system, and this effect saturates after about 20 years. So, for better economic operation of the hybrid system, the preferred lifetime of the plant should not be less than 20 years.

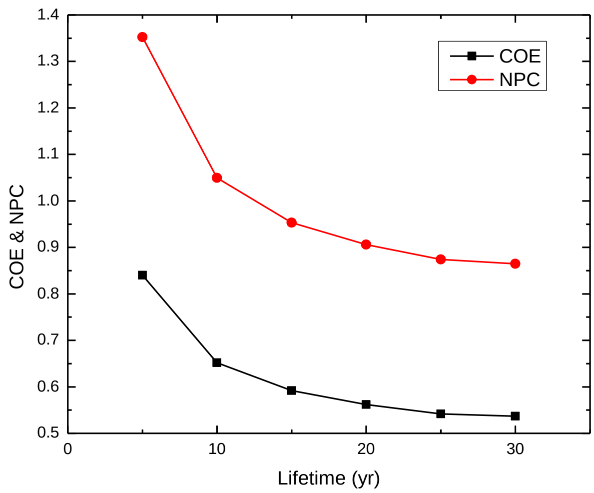


Fig 5.14: Hybrid system lifetime vs COE and NPC

5.4.5 Sensitivity analysis of the best scenario:

This sensitivity analysis is also done to study the variation of the expected economic performance within the domain of possible variations of input parameters. The impact result is shown in Fig. 5.15.

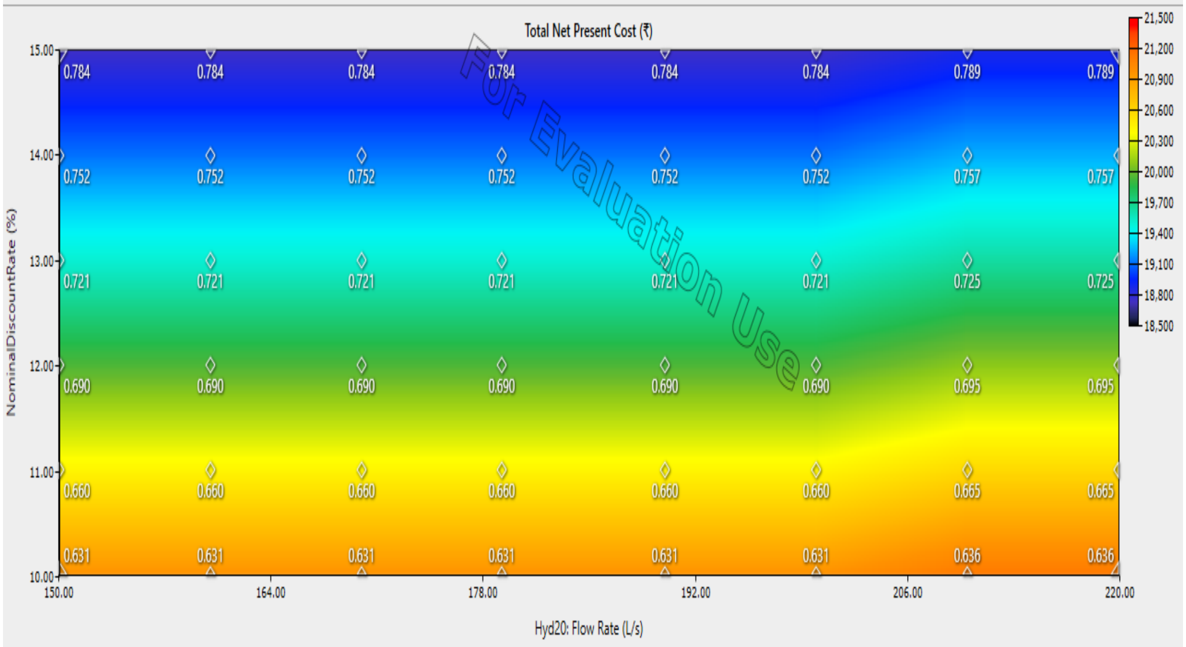


Fig 5.15: Effects of Flow rate and discount rate on COE and NPC

In Fig. 5.15 the influences are visible. This surface plot represents the NPC of the model with the superimposed condition of the COE. With the increase in the discount rate from 10% to 15% at a constant hydro flow rate of 150 l/s, the system's COE increases from \$0.631/kWh to \$0.784/kWh and the NPC decreases simultaneously from \$20,900 to \$18,500. If the discount rate increases then the COE increases. In spite of this, the NPC decreases making the system economically more feasible. It is because the effect of the discount rate on the COE is the reverse of the effect on the NPC. So, it is desired that the discount rate has a suitable value, so that the system's COE and the NPC both are retained at acceptable values. It will make the system economically feasible. If the hydro flow rate changes from150 l/s to 220 l/s at a constant discount rate (say 12.5%), it is clearly visible from Fig. 16 that the COE remains constant up to a hydro flow rate of 200 l/s but after 200 l/s it increases slightly from \$0.721/kWh to \$0.725/kWh. This suggests that if the hydro flow rate is low then it favors the economy of the electricity from the system. With the increase in the hydro flow rate, both the COE and the NPC increase. Thus, to make the system economic it is desired to maintain the hydro flow rate below 200 l/s throughout the year.

5.5 Summary of the chapter:

This study explores feasibility and techno-economic (including CO_2 emission penalty) performance assessment of a distributed hybrid renewable electricity system at a remote site with no grid power. Results show that a hybrid system consisting of wind-hydro with battery storage and a DG backup emerges as the optimal feasible solution for this site with a COE of \$0.63/kWh and CO_2 emission of 481 kg/year. This optimal combination emits 87% less CO_2 than only DG based systems for the same load demand. This combination is considered an economically and environmentally sustainable solution to meet the local load demand without any interruption.

CHAPTER- 6

Techno-economic and environmental impact assessment of decentralized HESs*

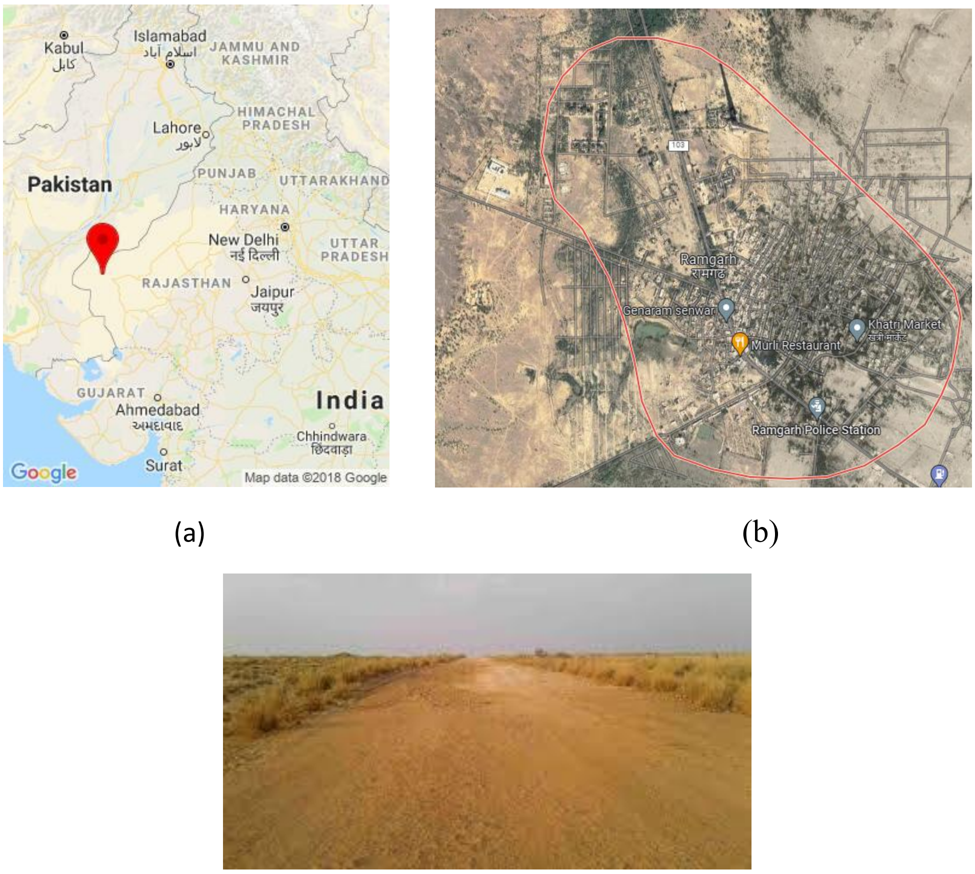
(***Das, S.**, De, S.* (2023): Technically efficient, economic and environmentally benign hybrid decentralized energy solution for an Indian village: multi criteria decision making approach. **Journal of Cleaner Production (Elsevier) (Published).** DOI: https://doi.org/10.1016/j.jclepro.2022.135717)

6.1 Objective of the work:

This study is aimed to perform both techno-economic optimization and detailed life cycle assessment (LCA) of the combinations to obtain a potential sustainable solution. In this work a detailed methodology is presented to practically determine a feasible optimum decentralized energy solution. However, for a better sustainable solution combining these three criteria is critical, specifically for poor villagers of a country like India. A comprehensive techno-economic analysis is followed by another comprehensive LCA. Unfortunately, independent solutions for minimum cost and best environmental performance may not be the same. A practical approach may be to adopt MCDM with proper weight factors assigned to these multiple criteria. Finally, the sensitivity analysis is performed using another MCDM approach to evaluate the robustness of the obtained solution.

6.2 Details of the study area:

The chosen location is Ramgarh village which is situated in Jaisalmer district, Rajasthan, a western state of India (shown in Fig. 6.1). The latitude and longitude of this location are 27°22.5’ N and 70°29.6’ E respectively (Kumari, 2011). The nearest town to this village is Jaisalmer which is 65 km away from the village. The households and the population of this village are 1400 and 8000 respectively (Chandramouli, 2011). The location has enough renewable resources (average solar irradiance- 7.99 $kWh/m^2/d$, temperature is 28.20°C and wind speed is 6-7.5 m/sec) (National Renewable Energy Laboratory (NREL). 2022).



(a) (b)

(c)

Fig. 6.1. (a) Location in Indian map, (b): Geographical location and (c) topographical condition (Kumari, 2011, Chandramouli, 2011)

6.3 Materials and Methodology:

Hybrid system capacity is determined for a minimum cost through techno-economic optimization. Environmental impact is then evaluated using LCA. The MCDM approach is finally integrated with the methodology to determine the feasible energy combination. The schematic diagram of the energy combination is shown in Fig. 6.2.

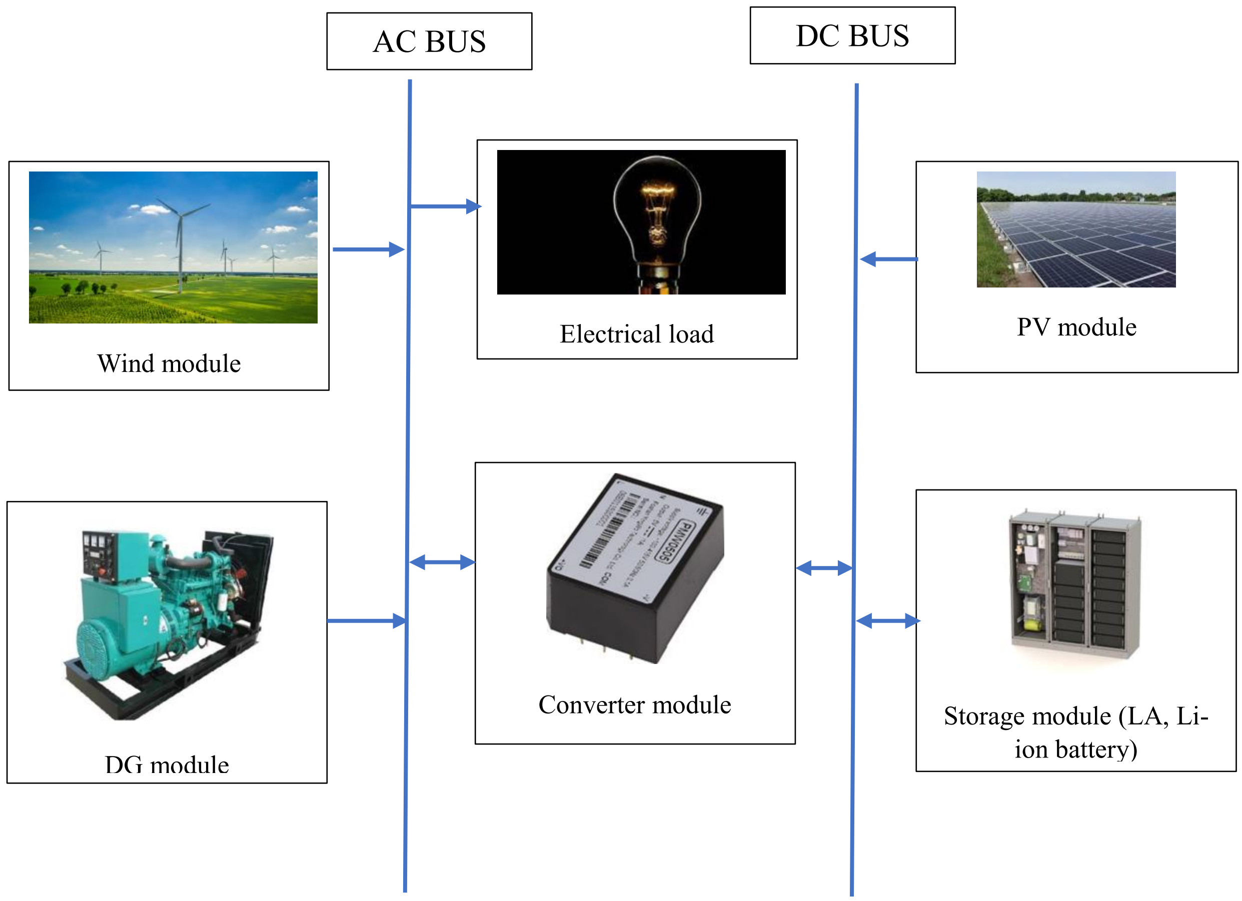


Fig. 6.2: Schematic Diagram of the energy combination

6.3.1 Solar PV modelling:

The output power of the PV module is discussed in equations shown in Table A. 1, Sl. No.: 1, Eqs. i-iii (Babatunde et al., 2022; Emad et al., 2021; Mandal et al., 2018) in Supplementary Index (SI).

6.3.2 Wind turbine modelling:

The output power of the wind module is discussed in equations shown in Table A. 1, Sl. No.: 2, Eqs. i-iii (Emad et al., 2021) in SI.

6.3.3 Modelling of Diesel Generator:

The equation of DG system is discussed in Table A. 1, Sl. No.: 5, Eq. i in SI (Ramesh & Saini, 2020).

6.3.4 Storage module modelling:

The equations of storage systems are discussed in Table A. 1, Sl. No.: 4, Eqs. i-v in SI (Baneshi & Hadianfard, 2016).

6.3.5 Converter modelling:

The equation of the converter system is discussed in Table A. 1, Sl. No.: 6, Eq. i in SI (Emad et al., 2021).

6.4 Input parameters and the objective function:

The objective function of the optimal solution of this study is defined to minimize the cost and environmental impacts and maximize the technical efficiency for better resource utilization. The load demand, techno-economic specifications of the components and weather resource data are provided as input parameters as discussed below.

6.4.1 Load estimation:

The load demand of the study area depends on the total population, lifestyle of those people, climate conditions and a few other socio-economic factors. In this study the load assessment is done for 50 households of this area. From previous reports published by the Central Electricity Authority (CEA) of India and from other published documents the electricity demand of this area is estimated (Dimock, 2019; Power Grid Corporation of India Ltd., 2013). In this study area, only two seasons, viz., summer and winter seasons are dominant. The load is estimated in kWh for these two seasons (Ramesh & Saini, 2020). According to the calculations, the total load is approximately 382.700 kWh/d in summer and 290.700 kWh/d in winter. The total yearly load demand is 336.700 kWh/d with an average load of 14.03 kW. The peak load and the load factor are 35.030 kW and 0.400. The typical daily load distribution is shown Fig. 6.3.

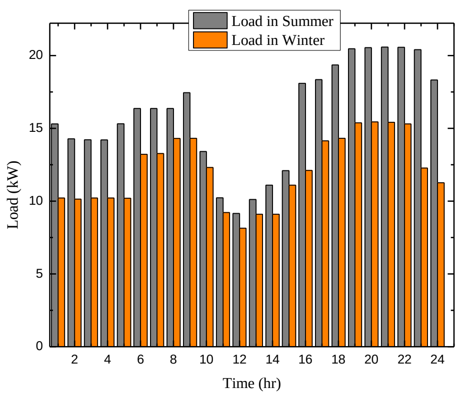


Fig. 6.3: Load distribution curve for a day (Ramesh & Saini, 2020)

6.4.2 Component's techno-economic details and resource assessment:

6.4.2.1 Solar energy data and PV module's specifications:

The solar radiation, clearness index and temperature data of this area is gathered from the National Renewable Energy Laboratory (NREL) website (National Renewable Energy Laboratory (NREL). 2022). The resources are shown in Fig. 6.4. The average solar radiation in this locality and the temperature of this area are 7.99 kWh/m^2/d and 28.20°C respectively.

Considering the solar resource in the study area, SG310MBF flat plate solar module has been considered. The detailed techno economic specifications of this module are shown in Table 6.1 (Gul et al., 2022; Raman Kumar & Channi, 2022; Malik et al., 2021)

6.4.2.2 Wind resource data and Wind turbine specifications:

The region being nearer to the desert, the wind speed there is also high. The wind speed at this location has a range of 6-7.5 m/sec during the entire y which is shown in Fig. 6.4. The data is collected from the NREL website (National Renewable Energy Laboratory (NREL). 2022).

Generic 3 kW wind turbines are used in this study. The cut-in and cut-out speeds of the wind turbine are 3.4 m/sec and 25 m/sec respectively. Other techno-economic details of this module are provided in Table 6.1 (Nag & Sarkar, 2018).

6.4.2.3 Battery module specifications:

Two different storage modules are compared in this analysis, i.e., LA and Li-ion batteries. Previous studies compared techno-economic aspects of these storage modules and confirmed their suitability (Ramesh & Saini, 2020). Storage modules can operate properly about 10 y with adequate maintenance. It is due to continuous degradation during operation (Ramesh & Saini, 2020). The techno-economic specifications of these storage devices are shown in Table 6.1 (Khan et al., 2021; Malik et al., 2021).

6.4.2.4 Diesel generator specifications:

The small capacity DG module is considered in this study to pursue the analysis. The techno-economic parameters of this module are shown in Table 6.1 (Khan et al., 2021; Malik et al., 2021).

6.4.2.5 Converter specifications:

In this hybrid system, a converter is required. The techno-economic specifications are discussed in Table 6.1 (Khan et al., 2021; Malik et al., 2021).

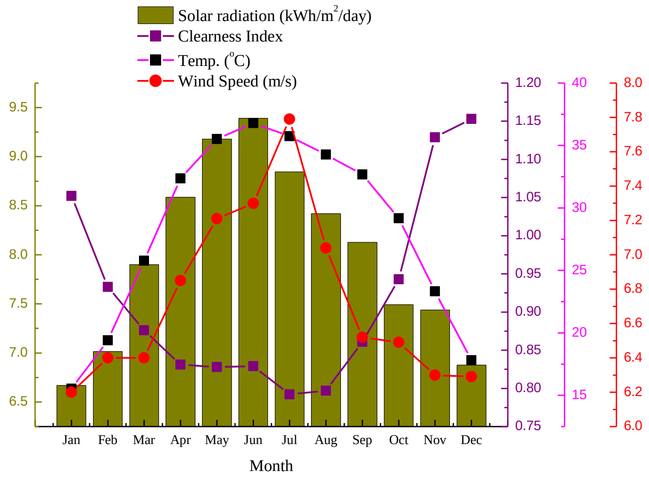


Fig. 6.4: Energy resource data (National Renewable Energy Laboratory (NREL). 2022)

Table 6.1: Component's techno-economic specifications (Kumar and Channi, 2022; Malik et al., 2021;Gul et al., 2022; Ramesh and Saini, 2020; Khan et al., 2021):

Sl. No.	Module Parameters	Specifications	Wind turbine Parameters	Specifications	Storage parameters	Specifications (Lead -acid battery (LA battery))	Specifications (Lithium- ion (Li-ion battery))	Diesel generator Parameters	Specifications	Converter Parameters	Specifications
1	PV module type	Peimar SG310MBF	Rated capacity (kW)	3	Nominal Voltage (V)	12	3.7	Capacity (kW)	1	Capacity (kW)	1
2	Efficiency at standard condition (%)	19.1	Rotor diameter (m)	4.26	Nominal Capacity (Ah)	83.4	276	Minimum load ratio (%)	25	Efficiency (%)	95
3	Ground reflectance (%)	20	Number of blades	3	Minimum state of charge (%)	40	20	Lifetime (h)	15,000	Lifetime (y)	15
4	Tracking system	Yes	Hub-height (m)	17	Round trip efficiency (%)	80	90	Fuel consumption rate ($/L)	1.5	Current charge (A)	21
5	Panel Slope (degrees)	27.37	Cut-in wind speed (m/s)	3.4	Lifetime (y)	10	20	Fuel curve intercept (L/h)	0.480	Output frequency (Hz)	50
6	Panel type	Flat plate	Cut-out wind speed (m/s)	25	Capital cost ($/Ah)	250	190	Fuel curve slope (L/h/kW)	0.286	Operating current maximum (A)	21
7	Derating factor (%)	80	Rated wind speed (m/s)	12	Replacement cost ($/Ah)	200	150	L.H.V. (MJ/kg)	43.200	Nominal operating input voltage DC (V)	110- 290
8	Operating Temperature (ºC)	25	Capital cost ($/kW)	1200	Operation and maintenance cost ($/y)	2	0	Capital cost ($/kW)	250	Capital cost ($/kW)	116
9	Temperature Coefficient	-0.4	Replacement Cost ($/kW)	980	Degradation (%)	0.2	0.2	Replacement cost ($/kW)	160	Replacement cost ($/kW)	116
10	Capital cost ($/kW)	741	Operation and maintenance cost ($/kW/y)	10				Operation and maintenance cost ($/y)	0.050	Operation and maintenance cost ($/y)	3
11	Replacement Cost ($/kW)	741	Lifetime (y)	20							
12	Operation and maintenance cost ($/kW/y)	25									
13	Lifetime (y)	30									
14	Degradation (%)	0.8									

6.4.3 Objective function and design parameters:

The objective function for optimization is formulated using the economic parameters: cost of electricity (COE), net present cost (NPC), operation and maintenance cost (O&M); technical factors: technical efficiency (TE) and environmental impact assessment using LCA. The COE and NPC are estimated using annualized cost, capital recovery factor (CRF) and yearly electricity consumption (Khan et al., 2021). O&M cost is the total cost of operation for each module. Technical efficiency of the system is measured on the basis of generated excess electricity (EE) (Nag & Sarkar, 2018). The comprehensive LCA is performed to obtain the environmental impact of each module considered in this study. The details of design parameters are discussed in this section.

6.4.3.1 Annualized cost:

The annualized cost is shown in Eq. i, in Table A.2, Sec. 2.i of SI.

6.4.3.2 Net present cost (NPC):

The NPC is shown in Eqs. i-iii, in Table A.2, Sec. 2.i of SI.

6.4.3.3 Cost of electricity (COE):

The COE is shown in Eq. i, in Table A.2, Sec. 2.ii of SI.

6.4.3.4 Excess electricity (EE):

The EE is shown in Eq. ii, in Table A.2, Sec. 1.ii of SI.

6.4.3.5 Objective function:

The objective function of this study is defined by using the above-mentioned design parameters. The objective function is used to determine the optimal solution to meet the load demand of the study area with the possible best technical, economic and environmental performance as shown in Eq. 6.1.

$$f_{obj} = \min(COE, NPC, O\&M, EI) and \max(TE) \quad (6.1)$$

According to the National Renewable Act, 2015 the Government of India published regulations for decentralized generation to be technically efficient, economic and environmentally benign as far as possible (IEA & NITI Aayog, 2021; Khan et al., 2022). COE, NPC, O&M cost are factors related to the economy of the system. Environmental impact (EI) and technical efficiency (TE) are also included for optimization. The objective function for this optimization includes economy, technical efficiency and environmental benignity according to the Indian government guideline. Different methods are integrated in this study to satisfy this objective function.

6.4.4 Adopted methodology:

The detailed methodology of this work is shown in Fig. 6.5. The techno-economic analysis of the energy combinations is done in Hybrid Optimization of Multiple Energy Resources (HOMER®). Step-by-step calculations are required for techno-economic analysis. HOMER® also provides the capacity of the energy modules and the percentage of EE or the unmet load (UL) of different possible energy combinations. Subsequently, the comprehensive environmental impacts of the energy combinations are studied through the LCA. The LCA is performed in SimaPro9®. Finally, a MCDM method is used to determine the feasible energy solution which is able to meet the required load demand of the area at an optimum condition as defined by the decided objective function.

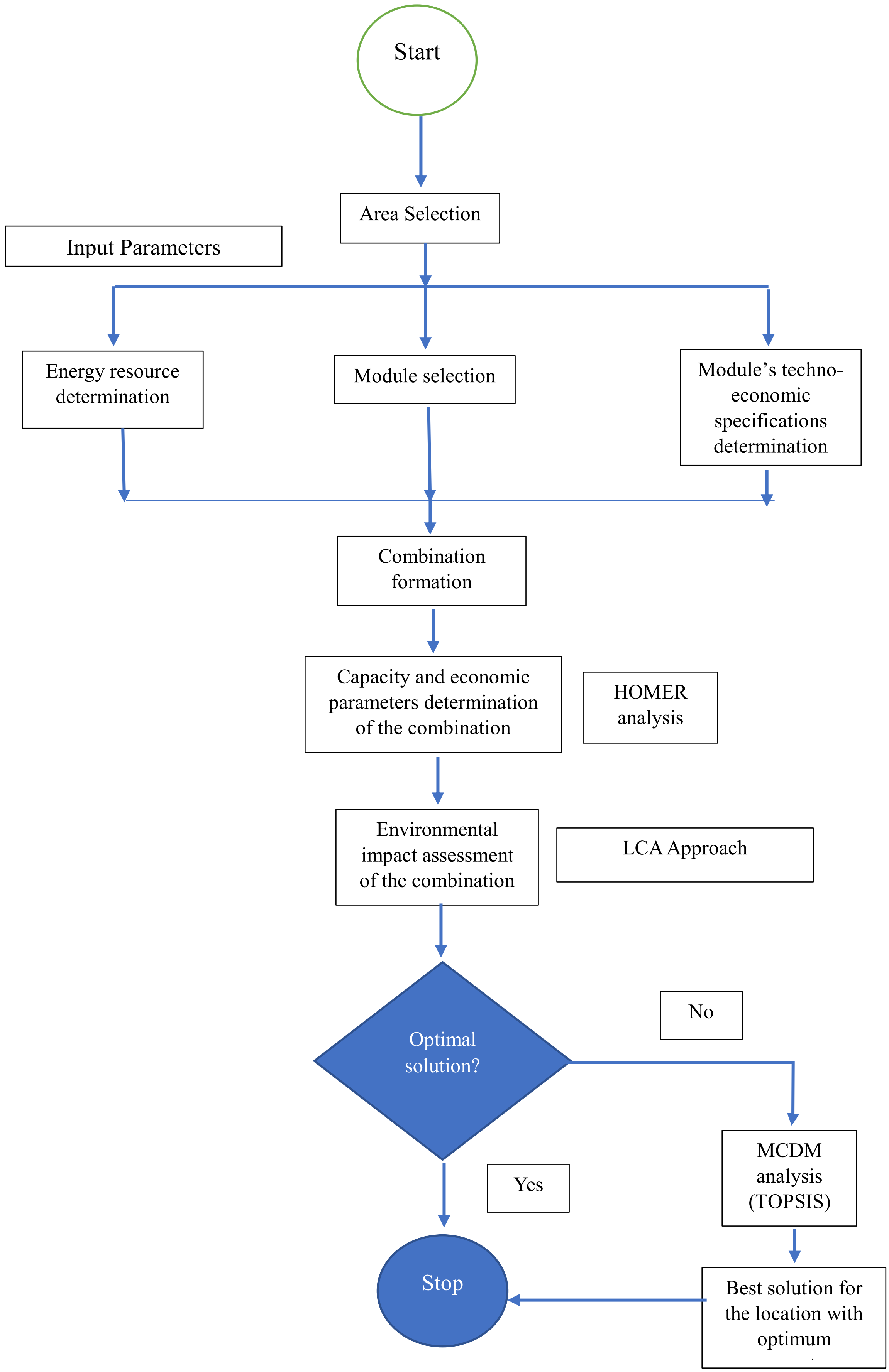


Fig. 6.5: Methodology flowchart

6.4.4.1 HOMER® simulation:

The detailed working principle of HOMER® is shown in Chapter 5, in "Sec. 5.3.3.1: HOMER® methodology" (Ramesh & Saini, 2020).

6.4.4.2 Dispatch strategy:

A dispatch strategy is a way to control and operate the storage and DG module when there is not enough renewable energy to satisfy the required load demand (Ramesh & Saini, 2020). Three dispatch strategies such as load following (LF), Cycle charging (CC) and combined dispatch strategy (CD) are available. In this study LF dispatch strategy is considered for the analysis because previous studies proved that this dispatch strategy is more beneficial than others (Ramesh & Saini, 2020). The working principle of the LF dispatch strategy is shown in Fig. 6.6. In this strategy the emission is less in this strategy as compared to other strategies.

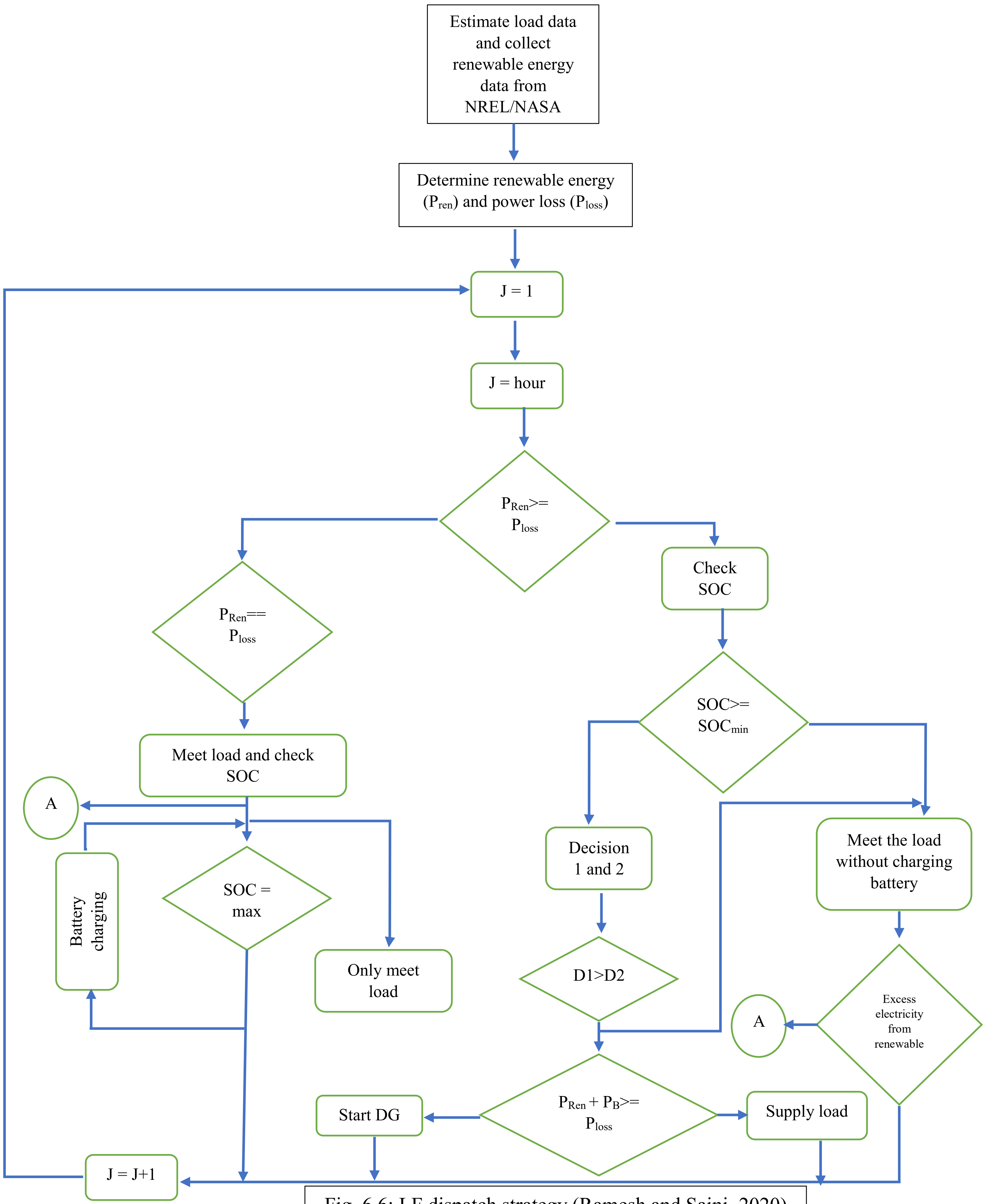


Fig. 6.6: LF dispatch strategy (Ramesh and Saini, 2020)

6.4.4.3 LCA methodology:

In this study LCA analysis is performed to evaluate the environmental impact of the hybrid energy system for examining the environmental sustainability in addition to techno-economic analysis. Environmental impact assessment using the LCA method has been conducted according to the ISO 14040/44 framework (Geneva: International Organization for Standardization; 2006). The mentioned framework consists of four interdependent steps i.e., goal and scope, data inventory analysis, impact assessment and interpretation (Ray et al., 2017). The results of HOMER® are considered as inputs to the LCA analysis.

6.4.4.3.1 Goal and Scope:

The 'Goal and Scope' of LCA analysis is the documentation step (Introduction to LCA with SimaPro Colophon, 2013). In this analysis the goal is to estimate the environmental impact for the overall life cycle of the designed hybrid energy combinations. These energy combinations are independent from central network systems.

In this study, the considered scope is 'cradle to grave'. Figure 6.7 shows the working principle to develop the system boundaries. The LCA comprises production of raw materials and component infrastructure, various parts assembly, transportation, installation, operation of systems, and end of life disposal. In this analysis, 1kWh of electricity produced is considered as a functional unit (FU) for LCA.

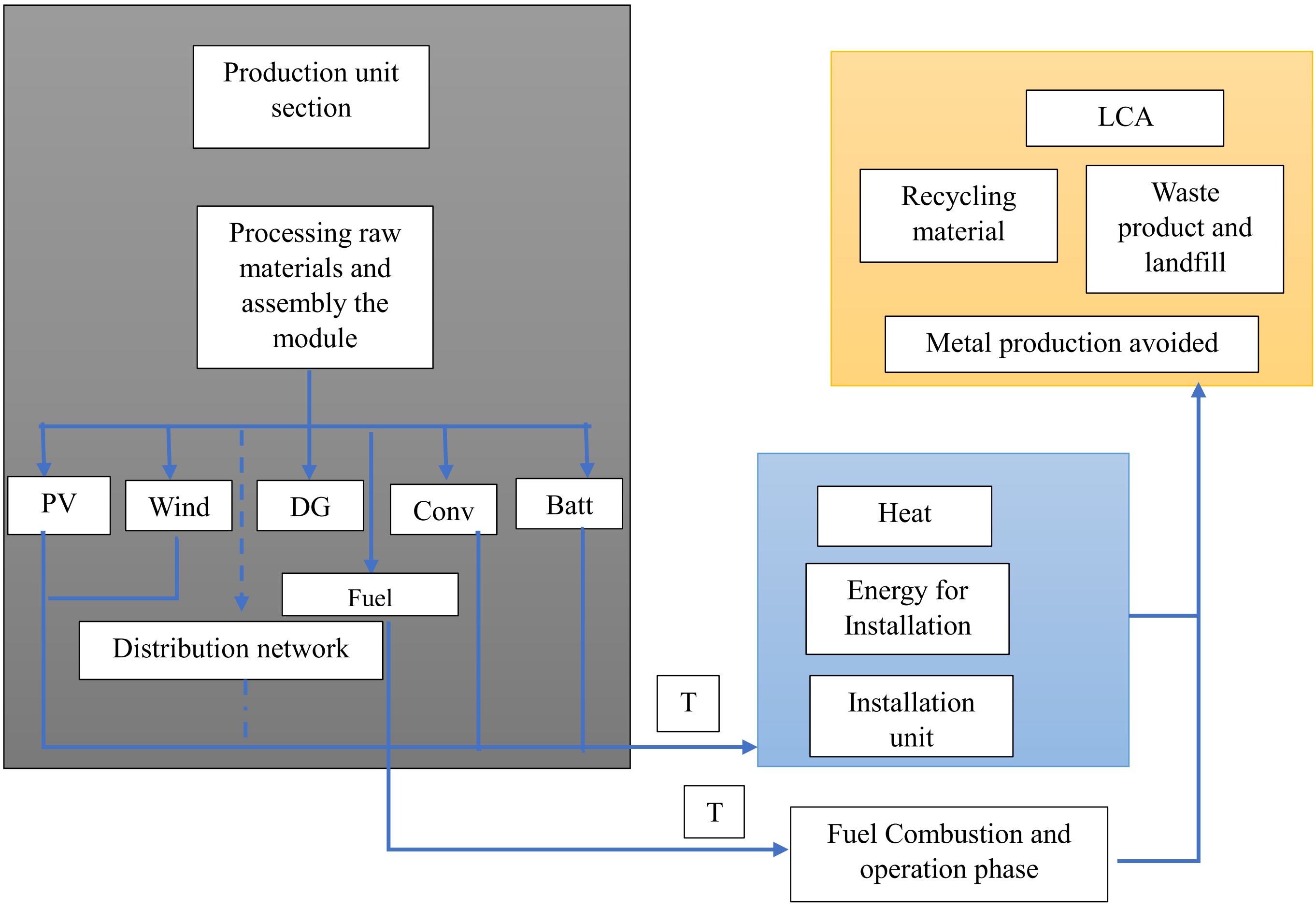


Fig. 6.7: Systems boundaries for the hybrid energy systems ("Introduction to LCA with SimaPro Colophon," 2013)

6.4.4.3.2 Data inventory:

6.4.4.3.2.1 Processing raw materials, assembling units, and installations:

Ecoinvent 3.1® database is considered for preparing the data inventory of the solar PV module, battery modules, converters and distribution network (Wernet et al., 2016). The raw material processing, installation and assembly of the data is done using this database. The sizing of the components has been calculated by HOMER®. Previous literature, data from the manufacturers were used to develop the inventory (Aberilla et al., 2020; Benton et al., 2017; Kabir et al., 2012; Spanos et al., 2015). These assembled data and other additional details are enlisted in Table 6.2-6.6.

Table 6.2: Data inventory of 1kg storage devices (LA and Li-ion) (Aberilla et al., 2020; Benton et al., 2017; Kabir et al., 2012; Spanos et al., 2015):

Lifecycle stage	**Storage module**	
	Lithium-ion (Li-ion)	Lead-acid (LA) battery
Installation		
Heat	-	6.7
Electricity (MJ)	0.7	4.6
Components and raw materials used		
Anode (kg)	0.312	0.3
Cathode (kg)	0.3	0.42
Electrolyte (kg)	0.14	0.2
Separator (kg)	0.04	0.03
Casing (kg)	0.15	0.08
Electronic (kg)	0.09	0.01

Table 6.3: DG system's data inventory (Aberilla et al., 2020; Benton et al., 2017; Kabir et al., 2012; Spanos et al., 2015):

Lifecycle stage	**Value**
Installation (GJ)	
Heat	65.3
Electricity	19.6
Components and raw materials (all units are in kg)	
$AlMg_3$, alloy of aluminium	32.8
Copper (Cu)	40.1
Cast iron	141
Cast alloy of Aluminium	31
Lead	0.7
Molybdenum	1.7
Epoxy resin (liquid)	3.3
High coal ferromanganese (74.5% MN)	6.1
Nickel (99.5%)	2.7
Wiring board (printed)	1.5
Pig iron	179.3
18/8 steel, chromium steel	2.5
Silicon carbide	146.7
Tin	0.5
Titanium	0.4
Low alloyed steel	498.3
Hot rolled low alloyed steel	121.9
Zinc	0.4

Table 6.4: Wind module' data inventory (Aberilla et al., 2020; Benton et al., 2017; Kabir et al., 2012; Spanos et al., 2015):

Lifecycle stage	**Value**
Raw materials of fixed part	
Reinforcing steel (kg)	9,100
Concrete normal (m^3)	80.83
Steel, low allowed (kg)	13, 100
Raw materials for moving parts	

Wrought allow aluminium (Al) in kg	260
Glass fibre in kg	1160
Copper in kg	910
Polyester resin, Unsaturated in kg	60
Steel, low allowed, hot rolled in kg	4680
Installation	
Diesel (MJ)	104.4
Explosive tovex (kg)	20.6

Table 6.5: PV module's data inventory (Aberilla et al., 2020; Benton et al., 2017; Kabir et al., 2012; Spanos et al., 2015):

Lifecycle stage	**Values**
Installation material	
Diesel as a fuel for mounting PV in ground (MJ)	1.74
Low voltage electricity for mounting PV in ground (MJ)	0.03
Low voltage electricity for roof mounting (MJ)	0.16
Raw materials for designing PV module	
Multi silicon waver for PV panel in m^2	1
Mounting system for PV module in m^2	0.97
Electrical parts for PV module in pieces	0.04

Table 6.6: Data inventory of converter (Aberilla et al., 2020; Benton et al., 2017; Kabir et al., 2012; Spanos et al., 2015):

Lifecycle stage	**Value**
Components for converter	
Cast alloy, Al in kg	1.4
Cu in kg	5.5
Capacitor in kg	0.6
Board box of Corrugated in kg	2.4
Glass diode in kg	0.05
Polyethylene fleece in kg	0.06
Clamp for electric connector in kg	0.24
Ring core choke type inductor in kg	0.35
Metal working factory in units	8.98E-09
Logic type circuit in kg	0.03
Slab of polystyrene in kg	0.3
Wiring box, printed in kg	0.225
Polyvinylchloride in kg	0.0011
Al section bar extrusion in kg	1.4
Steel sheet in kg	9.8
Resistor in kg	0.005
Hot rolled low alloyed steel in kg	9.8
Wired transistor in kg	0.04
Cu for wire drawing in kg	5.51
Styrene acrylonitrile copolymer in kg	0.01

6.4.4.3.2.2 Transport:

In the analysis, it is assumed that the components of each module are transported from different states of the country through railway and road. The detailed transportation is discussed in Table 6.7. Few components and Materials such as reinforcing steel and cement are procured locally.

Table 6.7: Transportation details:

Mode of transportation	Route	Distance in km
Railway, freight train (IN)	Factory to the urban warehouse	200
Road, freight lorry, 16-32 metric ton. Euro3	Urban warehouse to regional warehouse	160
Short distance road, freight lorry, 3.5-7.5 metric ton. Euro3	Regional warehouse to installation destination	100

6.4.4.3.3 Impact assessment:

The modelling of LCA and impact estimation have been carried out in SimaPro9® using method ReCiPe 2016 v1.1(M. A. J. Huijbregts et al., 2017). This LCA measures the impacts on human health, natural ecosystem and natural resources. According to ISO14040/44, this life cycle impact assessment is focused on understanding and evaluating magnitude and significance of the potential environmental impacts. In this LCA method, both the midpoint and endpoint indicators are considered. CML 2001 baseline is selected which implements the ISO 14040 standard and Eco-indicator 99®is used as the endpoint indicator. Eco-system quality, human health and resource scarcity are the three categories that assess impacts of the systems through this endpoint indicator. Midpoint indicators have been considered because the indicators have lower uncertainty and subjectivity. The 18 midpoint indicators are assessed to understand the impact of the system on the environment like climate change, water and soil pollution, eco-toxicity, resource depletion, land use and human health. The midpoint and endpoint indicators are discussed in detail in Tables. 6.8 and 6.9 (M. Huijbregts et al., 2016).

Table 6.8: Overview of the mid-point impact assessment characteristics (M. Huijbregts et al., 2016):

Environmental characteristics	Description	Unit
Climate change	It is the time horizon for the Egalitarian perspective that was taken for 1,000 years. These are CO2 response functions.	y/kg CO_2 to air
Stratospheric Ozone Depletion	It includes semi-empirical ozone depletion potentials with a more detailed specifications of chlorofluorocarbons (CFCs)	y/kg CFC11 to air

Ionizing Radiation	This is linked with the emission of radionuclides. It is majorly emitted during energy generation through fossil fuels such as coal.	y/kBq Co-60 to air
Fine particulate matter formation	The emission of particulate matter formation starts with the NO_x, SO_2, NH_3 and primary $PM_{2.5}$. It causes lung cancer and cardiovascular mortality	y/kg $PM_{2.5}$ to air
Photochemical ozone formation	This reports recent photochemical ozone formation potentials to evaluate the characterization factors for individual volatile organic compound	y/kg NO_X to air
Terrestrial acidification	This characterization factor describes soil sensitivity based on hydrogen concentration.	y/kg SO_2 eq
Freshwater eutrophication	This characterization indicates the result of the accumulation of nutrients in water bodies	Species.y/kg to air
Toxicity	This factor separately includes human cancer and non-cancer effects. The effects of dissociating organics were extensively modelled	y/kg 1,4-DCB to air
Land use	The local impact of land use was covered under this characterization factor	m2a crop eq
Mineral resource scarcity	Recovery of many metals were done through recycling. Sometimes recycling of metals unable to meet the demand. The characterization factor represents this.	kg Cu eq
Fossil resource scarcity	The scarcity of fossil fuel and the estimation of future production was included in the modelling	kg oil eq
Water consumption	Consumption ratio is provided. It is included in end-point level	m3

Table 6.9: Overview of the end-point impact assessment characteristics (M. Huijbregts et al., 2016):

Protection area	Endpoint	Abbreviations	Unit
Human health	It is the characterization factor to estimate the damages done on human health	HH	year
Natural environment	This measures the damage to ecosystem quality	ED	Species*y
Resource scarcity	Damages occurred to available resources	RA	Dollar

6.4.4.4 MCDM approach:

Multi-criteria decision-making (MCDM) approach is used to evaluate multiple conflicting alternatives in decision making. In other words, the MCDM approach is applied when multiple objectives need to be considered together and to choose or rank alternatives. In this study the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) MCDM algorithm is used to rank the feasible energy combination for the study area. The result of the TOPSIS approach is validated by another MCDM method. The ELimination Et Choix Traduisant la

REalite (ELECTRE) method is considered in this study for performing the sensitivity analysis. This method is widely used in different analyses (Alemi et al., 2011). This integrated MCDM approach helps to obtain a robust solution.

The TOPSIS algorithm was evolved by Hwang and Yoon in 1981 for finding the nearest and furthest alternative to the ideal and negative solution (Al Garni et al., 2016). The algorithm is discussed in Chapter 5, in "Sec. 5.3.3.2.1: TOPSIS_MCDM algorithm". The ELECTRE-MCDM method is used to evaluate the robustness of the result obtained through the MCDM approach described in steps.

It is an outranking method to deal with the situation in which a finite number of alternatives are needed to be ranked from the best to the worst (Alemi et al., 2011). The steps are applied as follows (Lin et al., 2021; Silvia et al., 2018):

Step 1: Derive the decision-making matrix X as represented in Eq. 6.2

$$X = \begin{bmatrix} a_{11} & a_{12} \cdots \cdots & a_{1n} \\ a_{21} & a_{22} \cdots \cdots & a_{2n} \\ \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \\ a_{n1} & a_{n2} & a_{nn} \end{bmatrix} \tag{6.2}$$

Where matrix element a_{ij} is the i-th alternative data with respect to the j-th criterion

Step 2: In this step normalize the raw data of the decision-making matrix.

Step 3: Construct the concordance sets matrix by using Eq. 6.3

$$J(A_i, A_j) = J^+(A_i, A_j) - J^-(A_i, A_j) \tag{6.3}$$

Where J^+ (A_i, A_j) is the criteria set for which the first alternative shows better result with respect to the second alternative, J^- (A_i, A_j) is the criteria set for which the first alternative shows equal performance with respect to the second alternative.

Step 4: Derive concordance indices matrix. The matrix corresponds to Eq. 6.4

$$C_{ij} = \frac{W^+(A_i, A_j) + W^-(A_i, A_j)}{\sum_k w_k} \tag{6.4}$$

Where W^+ (A_i, A_j) is the sum of the weights for the set J^+ (A_i, A_j), W^- (A_i, A_j) is the sum of weights for the set J^- (A_i, A_j) and w_k is the sum of all weights

Step 5: Develop concordance test matric by using Eq. 6.5

$$T_c(A_i, A_j) = \begin{cases} 1 \ \ if \ C_{ij} \geq C^* \\ 0 \ \ if \ C_{ij} < C^* \end{cases} \tag{6.5}$$

Where C^* is the fixed threshold value.

Step 6: Construct the discordance set matrix

Step 7: Construct the discordance indices matrix by using Eq. 6.6

$$D_{ij} = \begin{cases} 0 \ \ if \ J^-(A_i, A_j) = \cdots \\ max \ \{u_k(A_j) - u_k(A_i)\} \quad with \ k \in \ J^-(A_i, A_j) \end{cases} \tag{6.6}$$

Step 8: develop a non-discordance test matrix using Eq. 6.7:

$$T_D(A_i, A_j) = \begin{cases} 1 \ \ if \ D_{ij} \leq \ D^* \\ 0 \ \ if \ D_{ij} > D^* \end{cases} \tag{6.7}$$

Where D^* is the fixed threshold value.

Step 9: Finally, based on the concordance test matrix and discordance test matrix, the outranking matrix has been built by using Eq. 6.8

$$S\,(A_i, A_j) = \begin{cases} 1 \ \ if \ C_{ij} \geq C^* \ and \ D_{ij} \leq \ D^* \\ 0 \qquad\qquad otherwise \end{cases} \tag{6.8}$$

6.5 Results and Discussions:

Different combinations are formed using these storage modules and these combinations are compared in this analysis. Different factors are considered in this study to perform the analysis. Techno-economic factors of the combinations are analysed using HOMER®. The environmental impact assessment of these combinations is performed through the LCA approach. At the final stage, the TOPSIS-MCDM algorithm is used to select the optimal energy combination for the study area. The ELECTRE-MCDM method is used to evaluate sensitivity of the optimum solution obtained through the TOPSIS algorithm.

6.5.1 Designing energy combinations:

Initially, only renewable resources attached with storage modules are analysed. The techno-economic factors are compared. The technical factor is the UL and the economic factor is the COE. These are compared in the analysis. The result of this stage of analysis is shown in Table 6.10.

Table 6.10: UL and the capacity of different combinations:

Combinations	PV (kW)	Wind (kW)	LA battery	Li-ion battery	DG	UL	Cost of Electricity (COE-$/kWh)
DG-LA				320	39	0	0.79
DG-Li-ion			240		39	0	0.8
PV-LA	51.6		740			5.79%	0.0656
Wind-LA		61	1540			7.24%	0.0674
PV-Li-ion	51.1			390		3.57%	0.0601
Wind-Li-ion		41		1360		6.55%	0.0675
PV-wind-LA	36.5	18	620			4.92%	0.0686
PV-wind-Li-ion	36.5	16		420		2.93%	0.0666

Table 6.10 shows that out of different combinations only DG with LA and Li-ion storage module systems meet the load demand with a COE of ($0.79/kWh) and ($0.8/kWh) respectively. The operational carbon di-oxide (CO_2) emissions from these systems are also high with respect to that of other combinations. The other combinations of single renewable resources with both the storage modules are unable to meet the load. The UL is maximum in the Wind-LA (7.24%) followed by the Wind-Li-ion (6.55%), PV- LA (5.79%), PV-wind-LA (4.92%). The minimum UL is for the combination of PV-wind-Li-ion systems (2.93%). The maximum COE is obtained for a Wind-Li-ion system ($0.0686/kWh). From the analysis it is observable that only single renewable resources with storage are unable to meet the load. The capacity determined in this study is optimal. Increasing the capacity of the renewable energy generators is able to meet the UL but it simultaneously increases the COE of the combination. The increased COE exceeds the COE of the currently existing only DG based systems. Therefore, attaching DG systems with the developed combinations is the only solution to satisfy the required demand at an affordable price to the local people. In the next step, the combinations of renewable systems with the DG and storage modules are formed. The optimization is performed to obtain optimal size of the hybrid combinations for the best economy.

The developed combinations are PV-DG-LA, PV-DG-Li-ion, Wind-DG-LA, Wind-DG-Li-ion, PV-wind-DG-LA and PV-wind-DG-Li-ion. The economic performance factors are COE, NPC and O&M cost and the technical performance is evaluated on the basis of EE production. The generation of lesser EE is considered as a better efficient energy system. The objective of the optimization is to satisfy the load at an affordable cost and maximum efficiency. The economic analysis results are shown in Figs. 6.8-6.10 and the technical efficiency (EE analysis) result is shown in Fig. 6.11.

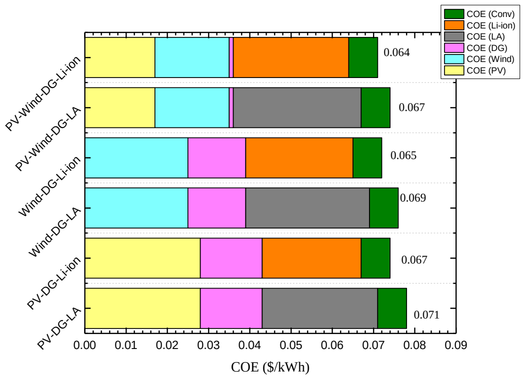


Fig. 6.8: COE analysis of the model

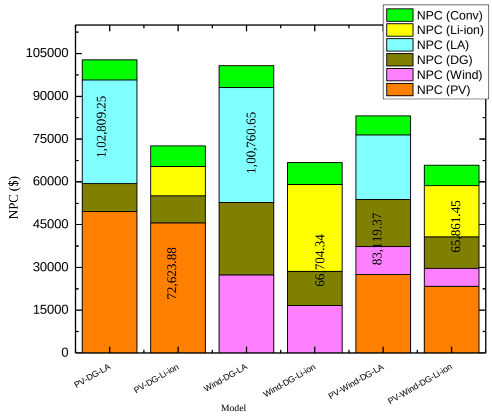


Fig. 6.9: NPC of the model

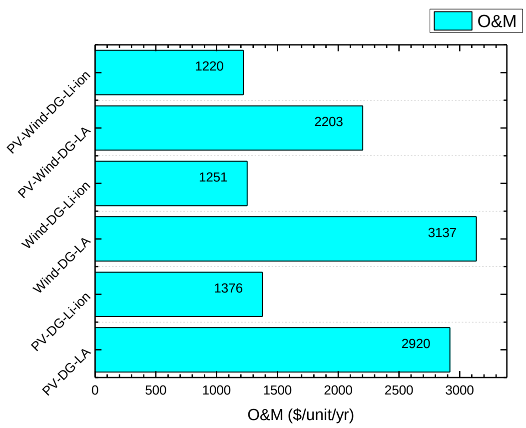


Fig. 6.10: O&M cost of the model

According to Fig. 6.8, the minimum COE is obtained for the PV-wind-DG-Li-ion combination ($0.064/kWh) followed by the Wind-DG-Li-ion ($0.065/kWh), PV-wind-DG-LA, PV-DG-Li-ion ($0.067/kWh), Wind-DG-LA ($0.069/kWh) and PV-DG-LA ($0.071/kWh). The NPC analysis is shown in Fig. 6.9. The analysis result shows that the NPC is minimum for PV-wind-DG-Li-ion ($65,861.45) and it is maximum for PV-DG-LA combination ($1,02,809.25). The analysis also highlights that the NPC share of PV modules is maximum followed by the LA batteries, wind module, Li-ion battery and DG system. In a PV-wind-DG-Li-ion based system the NPC share of PV is approximately 38.6%, Li-ion battery is 25.8%, wind module is 21.7%. The rest of the NPC is contributed by the DG and the converter. The O&M cost is also minimum for PV-wind-DG-Li-ion systems ($1220/kW/y). The economic analysis shows that the PV-wind-DG-Li-ion module is the economic solution as compared to the other combinations.

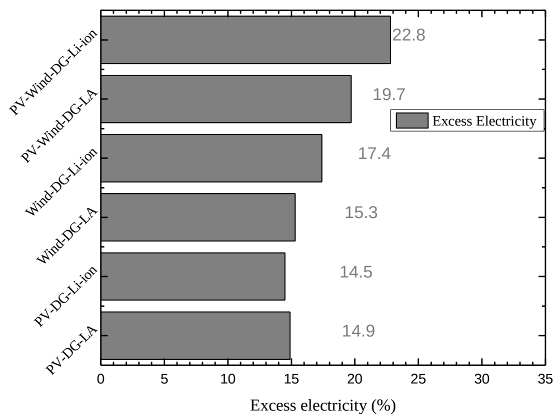


Fig. 6.11: EE percentage value of the hybrid system

The optimization study shows that the EE is maximum for the PV-wind-DG-Li-ion system (22.8%) followed by that of the PV-wind-DG-LA (19.7%), Wind-DG-Li-ion (17.4%), Wind-DG-LA (15.3%), PV-DG-LA (14.9%), PV-DG-Li-ion (14.5%). According to the objective of the study, the technical efficiency is maximum for the combination of PV-DG-Li-ion systems and minimum for PV-wind-DG-Li-ion systems. After performing the techno-economic optimization the LCA of the energy combinations is performed.

6.5.2 Environmental impact assessment:

The study evaluated the detailed environmental impact of the considered energy module combinations. The LCA analysis of the energy system is performed up to the project lifetime, which is considered as 25 years in this study. The eight different energy combinations such as PV-DG-LA (1st lifecycle), Wind-DG-LA (2nd lifecycle), PV-DG-Li-ion (3rd lifecycle), Wind-

DG-Li-ion (4th lifecycle), PV-wind-LA-DG (5th lifecycle), PV-wind-Li-ion-DG (6th lifecycle), DG-LA (7th lifecycle) and DG-Li-ion (8^{th} lifecycle) are considered for this analysis. The only DG system is considered as the reference case for comparing the environmental performance improvement. The environmental impacts of these combinations are studied using the LCA method which is performed in SimaPro9®. Both the midpoint and the endpoint analyses are performed. The ReCiPe 2016 midpoint (H) is used for the midpoint analysis and the ReCiPe 2016 endpoint (E) is used for the endpoint analysis. The midpoint analysis provides all the above-mentioned characterization factors. The normalization values of this analysis are shown in Fig. 6.12. The actual numerical values of these factors are given in Table 6.11.

The figure shows that the combination of wind-DG-LA has the highest impact (30930678 kg CO_2 eq) under global warming criteria followed by the wind-DG-Li-ion, DG-LA, DG-Li-ion, PV-wind-DG-LA and PV-wind-DG-Li-ion systems. The minimum global warming impact is found for the combination of PV-DG-LA and PV-DG-L-ion systems. The emissions from these two combinations are 15286309 kg CO_2 eq. and 15282442 kg CO_2 eq. respectively.

The DG-LA and DG-Li-ion combinations have the highest impacts under the criteria of stratospheric ozone depletion. The values of these two components are 35.97 kg CFC11 eq. and 35.96 kg CFC11 eq. The minimum impact under this criterion is found in PV-DG-Li-ion (23.58 kg CFC11 eq.) combination.

A similar result is obtained for the criteria of ionizing radiation. The minimum impact is found in the combination of PV-Li-ion-DG (913202.4 kBq Co-60 eq.). The maximum impact is found in the DG-Li-ion combination (1374132 kBq Co-60 eq.) followed by the DG-LA (1373900 kBq Co-60 eq.), PV-wind-DG-Li-ion (1004153 kBq Co-60 eq.), PV-wind-DG-LA (1036630 kBq Co-60 eq.),

For fossil fuel scarcity and water consumption criteria the DG-Li-ion combination has the maximum impact (46055841 kg oil eq. and 283929.5 m^3 respectively). The minimum impact is found for the combination of PV-Li-ion DG (30519378 kg oil eq. and 189390.1 m^3).

For the criteria of ozone formation, the minimum impact is obtained in the PV-DG-Li-ion combination and the maximum impact is found in the Wind-DG-LA system. The impact in minimum combination is 45.56%-47% lesser as compared to the combination of the wind-DG-LA system.

A similar result is obtained for the other midpoint characteristics such as fine particulate matter formation, terrestrial acidifications, freshwater eutrophication, marine eutrophication, terrestrial ecotoxicity, freshwater ecotoxicity, marine ecotoxicity, human carcinogenic and non-carcinogenic toxic. The minimum impact is found in the PV-DG-Li-ion energy combination. The impacts are 43.21%, 37.3%, 77.1%, 73.42%, 82%, 85%, 84.7%, 84.71%., 81.55% less as compared to those of the wind-DG-LA combination which has the maximum impacts under these criteria.

In land use and mineral resource characteristics the impacts of the wind-DG-LA combination are 84.7% and 83% respectively more than that of the PV-DG-Li-ion combination.

The endpoint analysis summarizes the 18 midpoint characterization factors into three different criteria such as human health, ecosystems and resource scarcity. The result of these endpoint analysis for the 8 combinations is shown in Fig. 6.13.

The endpoint analysis shows that the Wind-DG-LA system has the maximum impact on the human health and ecosystem (4074.896 and 2.59 respectively) followed by Wind-DG-Li-ion (2837.36 and 1.86 respectively). In these two characteristics the impact is less for the combination of PV-DG-Li-ion (909.77 and 0.74). For these two criteria the impacts of PV-wind-DG-LA and PV-wind-DG-Li-ion are more as compared to those of the DG-LA and DG-Li-ion. For resource scarcity, the impact is maximum for the DG-LA and DG-Li-ion combinations followed by the Wind-DG-LA, Wind-DG-Li-ion, PV-wind-DG-LA and PV-wind-DG-Li-ion. The DG-LA and DG-Li-ion combinations used the fossil fuels and the chance of fuel depletion is high for the fossil fuel-based systems. In DG based energy combinations the resource scarcity is high. The combination of PV-DG-Li-ion is the best for this characteristic. The exact value of the analysis is shown in Table 6.12. From this comparison it is observed that the combination of PV-DG-Li-ion has the minimum environmental impact as compared to those of the other energy combinations.

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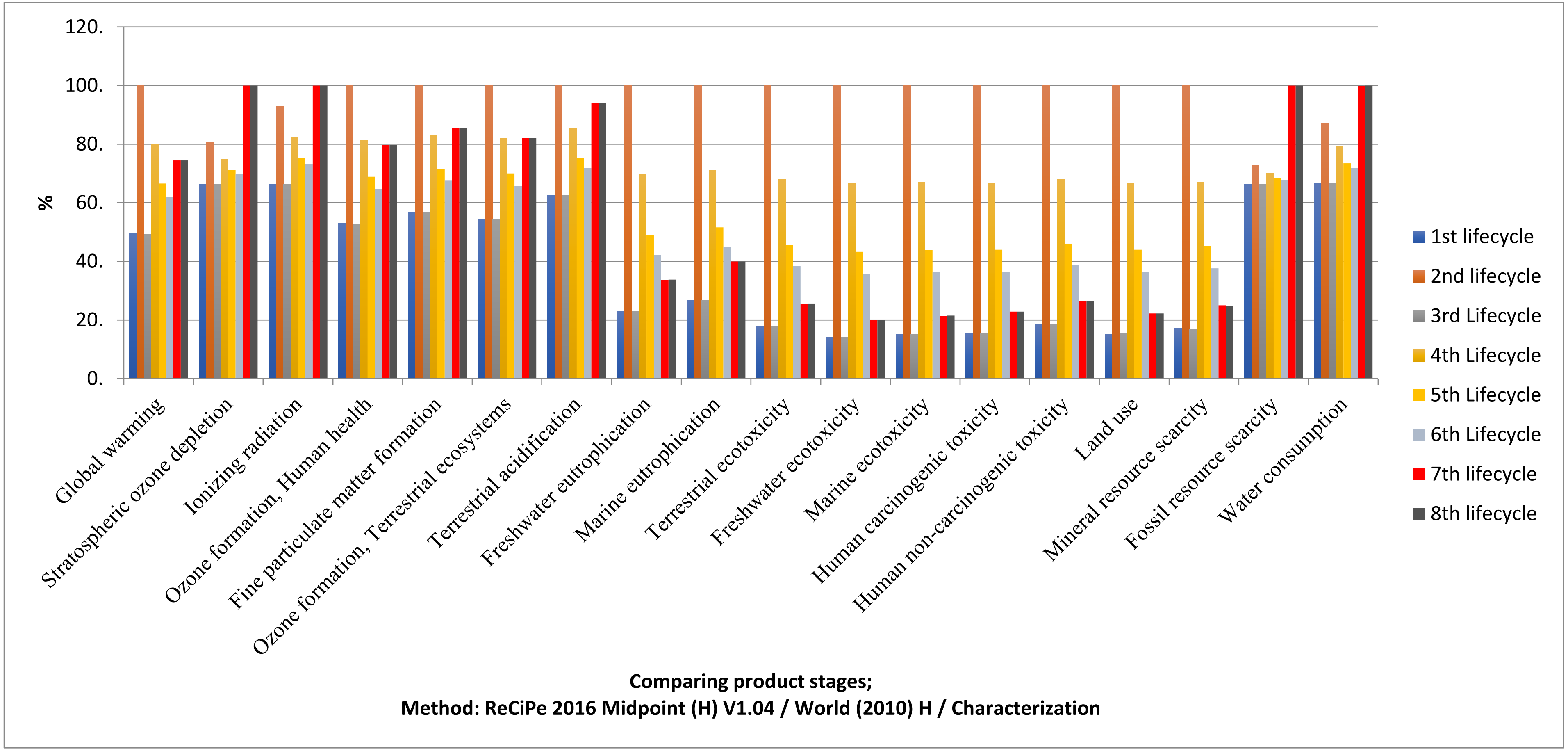


Fig. 6.12: Environmental impact of hybrid energy combination in midpoint indicator

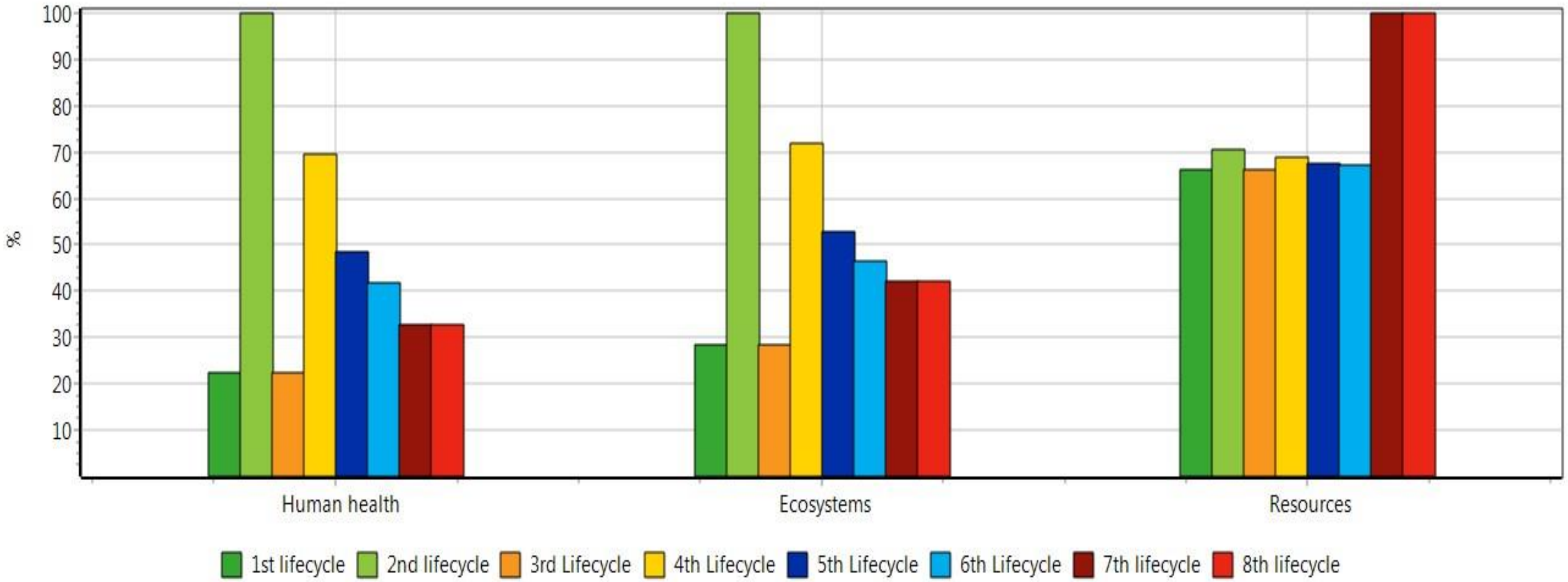


Fig. 6.13: Environmental impact analysis in End point indicator of hybrid combination

Table 6.11: Environmental impacts (exact values) in midpoint indicator analysis

Impact category	Unit	PV-LA-DG	Wind-LA-DG	PV-Li-ion-DG	Wind-Li-ion-DG	PV-wind-DG-LA	PV-wind-DG-Li-ion	DG-LA	DG-Li-ion
Global warming	kg CO2 eq	15286309	30930678	15282442	24771319	20587261	19186109	23036446	23037651
Stratospheric ozone depletion	kg CFC11 eq	23.85458	28.9648	23.85069	26.93817	25.58043	25.11738	35.96677	35.96827
Ionizing radiation	kBq Co-60 eq	913217.4	1278382	913202.4	1134671	1036630	1004153	1373900	1374132
Ozone formation, Human health	kg NOx eq	58642.91	110833.8	58632.81	90291.24	76326.68	71656.35	88369.81	88375.98
Fine particulate matter formation	kg PM2.5 eq	36679.97	64599.24	36679.93	53628.28	46133.75	43649.54	55153.62	55163.64
Ozone formation, Terrestrial ecosystems	kg NOx eq	63527.98	116694	63517.32	95765.68	81541.46	76783.14	95744.3	95750.67
Terrestrial acidification	kg SO2 eq	103454.2	165546.3	103458.9	141151.2	124473.1	118954.8	155592.5	155621
Freshwater eutrophication	kg P eq	2115.792	9245.454	2119.564	6457.678	4531.403	3904.619	3116.85	3121.044
Marine eutrophication	kg N eq	158.1307	589.4631	158.0761	419.956	304.2763	265.845	235.509	235.5618
Terrestrial ecotoxicity	kg 1,4-DCB	50936093	2.88E+08	51144153	1.96E+08	1.31E+08	1.11E+08	73686667	73872753
Freshwater ecotoxicity	kg 1,4-DCB	587303.8	4149609	591142.4	2762803	1794221	1484779	828435.4	831822.5
Marine ecotoxicity	kg 1,4-DCB	809316.9	5354807	814069.9	3584907	2349307	1954259	1148109	1152359
Human carcinogenic toxicity	kg 1,4-DCB	394883.6	2582911	394830	1723542	1136744	941746.3	589539.8	589794.5
Human non-carcinogenic toxicity	kg 1,4-DCB	10737997	58364974	10763097	39777997	26867375	22702272	15457016	15490794
Land use	m2a crop eq	1232073	8087442	1235803	5406790	3555699	2952433	1794516	1798156
Mineral resource scarcity	kg Cu eq	45335.35	261681.1	44483.5	175749.5	118366.2	98498.52	65495.32	65235.88
Fossil resource scarcity	kg oil eq	30525935	33493212	30519378	32297772	31523680	31246138	46055518	46055841
Water consumption	m3	189196.5	247919.7	189390.1	225339.4	208688.5	204073	283688.6	283929.5

Table 6.12: Environmental analysis of hybrid system in end point indicator

Damage category	PV-LA-DG	Wind-LA-DG	PV-Li-ion-DG	Wind-Li-ion-DG	PV-wind-DG-LA	PV-wind-DG-Li-ion	DG-LA	DG-Li-ion
Human health	908.356	4074.896	909.7782	2837.364	1981.008	1702.972	1330.716	1332.607
Ecosystems	0.738786	2.592296	0.739651	1.867786	1.366629	1.20384	1.091848	1.092979
Resources	13638513	14522523	13635454	14161721	13934485	13849723	20577615	20577657

From the detailed techno-economic analysis followed by the LCA of different energy combinations two different optimal solutions are obtained. The economic factors show that PV-wind-DG-Li-ion energy combination is the optimal. Whereas the technical analysis and LCA show that the PV-DG-Li-ion combination has the maximum efficiency and minimum environmental impact. It becomes difficult to obtain a single solution which is simultaneously techno-economically and environmentally optimal. The MCDM approach is used to decide the final optimal solution. The ELECTRE method is integrated to this optimization for the sensitivity analysis of the optimal solution obtained through the TOPSIS-MCDM approach.

6.5.3 MCDM analysis:

The MCDM analysis is performed at this stage to obtain the simultaneous techno-economic and environmentally optimal energy combination for the selected study area. In the detailed techno-economic and environment analysis two different optimal energy combinations are obtained as a solution. The economic assessment shows that the PV-wind-DG-Li-ion is the most economic combination with a COE \$0.064/kWh, O&M cost \$1220/kWh/y and NPC \$65861.45. Irrespective of the economical solution the technical efficiency of this combination is poor (22.8%). Whereas technically efficient (generated EE is 14.5%) and environmentally more sustainable energy combination is PV-DG-Li-ion. To determine the finally recommended optimal solution out of these two alternatives TOPSIS-MCDM is used. The decided criteria for selecting optimal alternatives are economic factors (COE, NPC, O&M cost), technical performance (i.e., technical efficiency) and LCA. In this study, equal weightage is given for the considered criteria. The decided weightage is 0.2 for each criterion. To measure the technical efficiency and LCA a scale has been proposed. The scale is shown in Table 6.13.

Table 6.13: scale of the analysis

Features	**Best**	**Good**	**average**	**Moderately low**	**Low**
Scale value	5	4	3	2	1

The decision makers may decide the technical and environmental scale values for alternatives according to their priority. The decision-making matrix is shown in Table 6.14. Table 6.15 shows the final ranks of the alternatives.

Table 6.14: Decision making matrix

Alternatives	Criteria				
	COE	NPC	Environmental impact assessment	O&M cost	Technical Efficiency
PV-DG-Li-ion	0.067	72623.88	5	1376	5
PV-Wind-Li-ion-DG	0.064	65861.45	2	1220	1
	0.092655	98040.6	4.472135955	1838.960576	5.385164807

Table 6.15: Performance score and Ranking Matrix

Alternatives	S^{+}_{J}	S^{-}_{J}	$S^{+}_{J} + S^{-}_{J}$	Performance Score	Rank
PV-DG-Li-ion	0.114323926	0.157	0.271324	0.578644	1
PV-Wind-Li-ion-DG	0.157	0.114324	0.271324	0.421356	2

The TOPSIS analysis shows that the PV-DG-Li-ion energy combination is the techno-economically and environmentally optimal option for this study. The output is validated using ELECTRE MCDM method. The output of the sensitivity analysis is shown in Table 6.16.

Table 6.16: sensitivity analysis (Outranking method) using ELECTRE

	Net superior	Rank	Net Inferior	Rank
M1	1	1	-1	1
M2	-1	2	1	2

The sensitivity analysis result shows that the PV-DG-Li-ion energy combination is the optimal solution. The same solution is obtained through TOPSIS analysis. The analysis concludes that the obtained optimal solution is robust. The technical efficiency of the combination is high for this combination as the EE is 14.5% which is the lowest out of all possible combinations. The COE, NPC and O&M costs are \$0.067/kWh, \$72623 and \$1376/kW/y respectively. The economic parameter values are also moderate for this combination as compared to other selected alternatives. The LCA analysis also shows that environmental impact is significantly less for this combination.

6.6 Summary of the chapter:

Determining the best possible hybrid decentralized energy solution through effective local resource utilization is a critical challenge. The objective of the study is to determine the technically efficient energy module combination for minimum cost and environmental impact simultaneously meeting the required load demand of the study area. As the possible solutions for the best techno-economic and environmental solutions may not be identical, a MCDM combining all these results with a decided weight factor for each is used. The comprehensive analysis results show that the PV-Li-ion-DG system is techno-economically and environmentally optimal solution for the decided location. The economic factors such as COE is \$0.067/kWh, NPC is \$72,623.88 and O&M cost is \$1378/kW/y for this combination. The generated EE is also less (14.5%) as compared to other combinations. The LCA approach shows that the combination is an environmentally optimal solution. The different LCA are lesser (by about 40.5-82%) for this combination as compared to the others. The result of the proposed integrated methodology provided this PV-Li-ion-DG combination as the techno-economically and environmentally feasible energy solution.

CHAPTER- 7

Techno-economic with least financial risk and environmental impact* decentralized HESs

(*<u>**Das, S.**</u>, De, S.* (2023): MCDM for simultaneous optimum economy, investment risk and environmental impact for distributed renewable power: demonstration with an Indian village data. **Energy Conversion and Management (Elsevier) (Published).** DOI: https://doi.org/10.1016/j.enconman.2022.116631)

7.1 Objective of the work:

The study is performed to decide an optimal solution which is technically efficient, economic with acceptable uncertainty in ROI and environmentally less impactful energy combination. There are uncertainties in ROI for these new technologies and scientific analysis may help investors to decide more confidently. This study combines economic analysis, risk assessment on economic investment and LCA for decentralized hybrid renewable systems. It is useful to assess the overall sustainability of such hybrid systems. However, final choice of the system may depend on assigned priorities of these independent assessments. A MCDM with assigned priorities may be used to decide the final optimum solution.

7.2 Materials and methodology:

The schematic diagram of the energy resource combination is shown in Fig. 7.1.

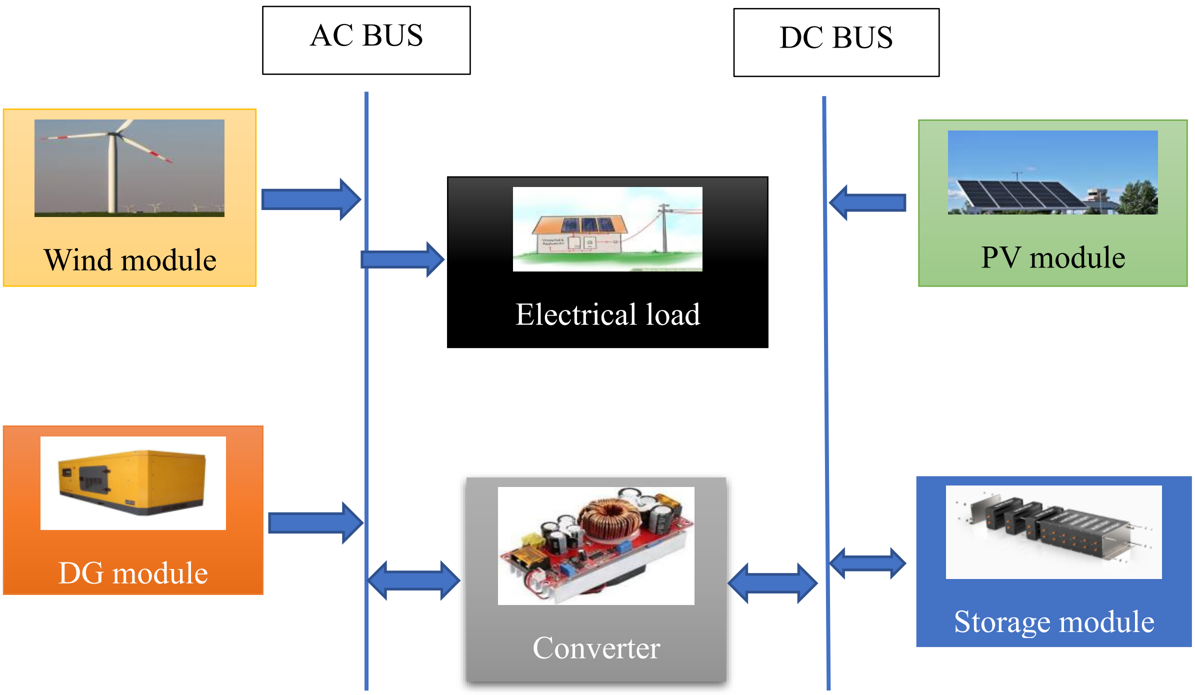
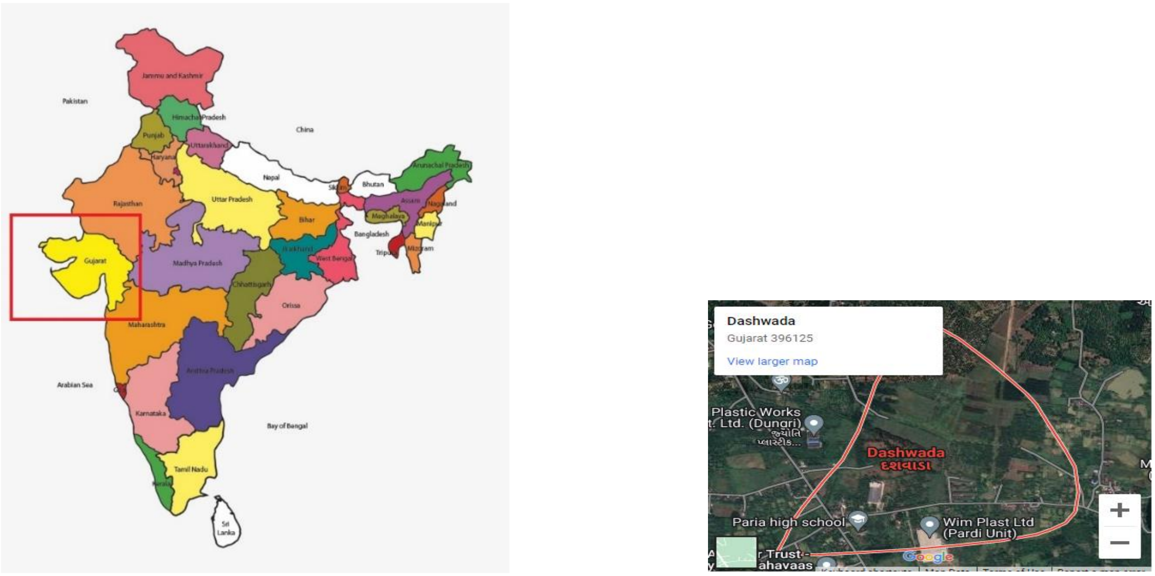


Fig. 7.1: Energy resource combination

7.2.1 Study area selection:

The study was performed at a remote village of Gujrat, the western state of India. The village name is Dashwada which is located in Pardi Taluka under Valsad district of Gujrat. The latitude and longitude of the location is 20º49'N and 72º55' E (NICEPNG, 2020). The location of this village is shown in Fig. 7.2 (Villageinfo.in, 2011). Villagers are suffering from no access to reliable and continuous power (Saiyed, 2020). The state has enough renewable resources and in wind energy production the state is second in the country (Express New Service, 2022). Also, the solar energy potential is high in this state (Express New Service, 2022).



(a) (b)

Fig. 7.2.a: Study area location, b. Detailed study area (Villageinfo.in, 2011)

7.2.2 Materials and input parameters:

Techno-economic specifications of the modules, load data, climate data like solar irradiance, wind speed, temperature of the study area etc. are considered as input parameters. The considered techno-economic performance indicators are COE, unmet load (UL) and renewable fraction (RF). According to Fig. 7.1 the considered materials in this study are solar PV module, wind module, storage device, converter and DG.

7.2.2.1 Solar PV module modelling:

The output power of the PV module is discussed in equations shown in Table A. 1, Sl. No.: 1, Eqs. i-iii (Babatunde et al., 2022; Emad et al., 2021; Mandal et al., 2018) in Supplementary Index (SI).

The flat plate 1 kW solar module Peimar SG290MFB is considered in this analysis (Ramesh & Saini, 2020). The other detailed techno-economic specifications are given in Table 7.1.

The solar radiation and temperature data of this location is collected from the NASA weather report (NASA, 2022a). The data is shown in Fig. 7.3. The average solar radiation of this location is 6.35 kWh/m^2/day and the temperature of this place is 26.78 ºC.

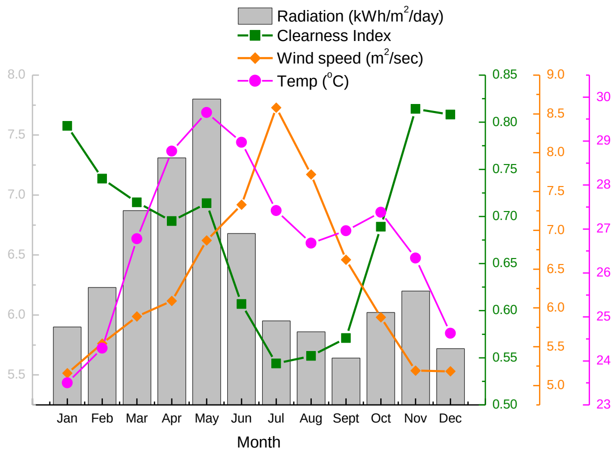


Fig. 7.3: Energy resource data (NASA, 2022)

7.2.2.2 Wind turbine modeling:

The output power of the wind module is discussed in equations shown in Table A. 1, Sl. No.: 2, Eqs. i-iii (Emad et al., 2021) in SI.

In this study, the generic 3 kW wind turbine is considered in this study. The details of the components are shown in Table 7.1 (Ramesh & Saini, 2020).

The wind speed of the study location is collected from the NASA website. The wind speed is shown in Fig. 7.3. The average wind speed was 6.34 m^2/sec (NASA, 2022a).

7.2.2.3 Storage module modelling:

The equations of storage systems are discussed in Table A. 1, Sl. No.: 4, Eqs. i-v in SI (Baneshi & Hadianfard, 2016).

In this study Li-ion storage modules are used (Ramesh & Saini, 2020). The detailed techno-economic data are provided in Table 7.1.

7.2.2.4 DG module modelling:

The equation of DG system is discussed in Table A. 1, Sl. No.: 5, Eq. i in SI (Ramesh & Saini, 2020).

The small-capacity DG is used in this analysis (Uwineza et al., 2021). The detailed specifications of the module are provided in Table 7.1.

7.2.2.5 Converter modelling:

The equation of the converter system is discussed in Table A. 1, Sl. No.: 6, Eq. i in SI (Emad et al., 2021).

The techno-economic specifications of the module is described in Table 7.1 (Ramesh & Saini, 2020).

Table 7.1: Techno-economic specifications of the components (Ramesh & Saini, 2020)

PV system (flat type)		**Wind turbine (Generic 3 kW)**		**Li-ion Battery**		**DG module**		**Converter module**	
Specifications	Data	Specifications	Data	Specifications	Data	Specifications	Data	Specifications	Data
Capital cost (US$/kW)	630	Capital cost (US$/kW)	1200	Capital cost (US$/kW)	190	Capital cost (US$/kW)	750	Capital cost (US$/kW)	300
Replacement cost (US$/kW)	0	Replacement cost (US$/kW)	1200	Replacement cost (US$/kW)	150	Replacement cost (US$/kW)	750	Replacement cost (US$/kW)	300
O&M cost (US$/kW/year)	15.75	O&M cost (US$/kW/year)	30	O&M cost (US$/kW/year)	8	O&M cost (US$/kW/year)	1.34	O&M cost (US$/kW/year)	3
Temperature coefficient	-0.42	Lifetime (years)	20	Nominal voltage (v)	6	Fuel curve intercept (L/hr)	2.79	Lifetime (years)	15
Operating temperature (°C)	25	Hub height (m)	17	Nominal capacity (Ah)	167	Fuel curve slope (L/hr/kW)	0.236	Efficiency (%)	95
Efficiency (%)	17.8			Efficiency (%)	90			Relative capacity (%)	100
Lifetime (years)	30			Charging and discharge current (A)	167 and 500				
Ground reflectance (%)	20			Lifetime (years)	15				
Tracking	No			Throughput (kW·h)	3000				

7.2.3 Methods:

The detailed methodology is shown in Fig. 7.4 as a flowchart.

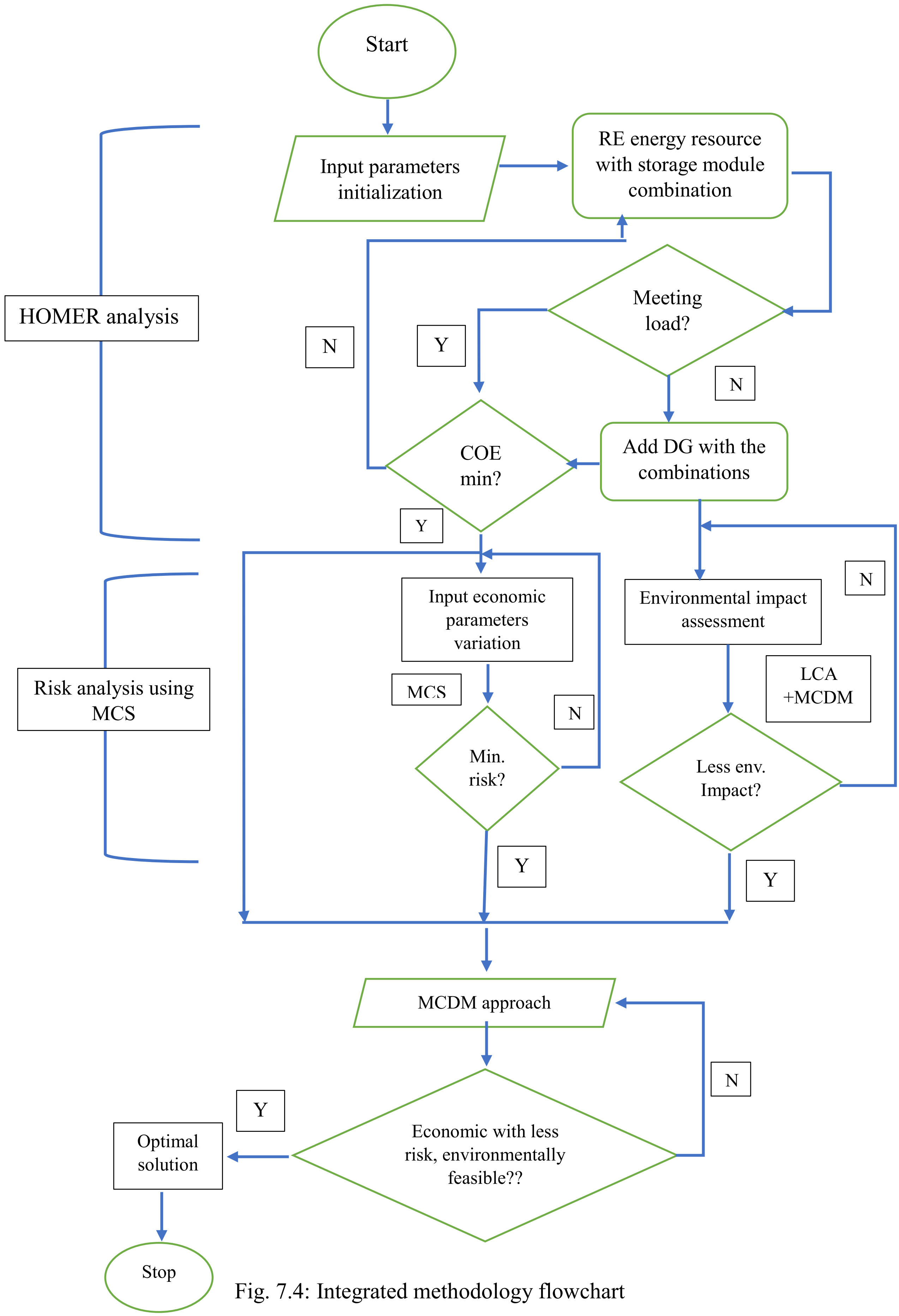


Fig. 7.4: Integrated methodology flowchart

HOMER® is used to find the energy combination through techno-economic analysis. To meet the load demand, input parameters and resource combinations are decided. The objective function is decided on the basis of the technical performance factor UL and the economic performance factor COE. Initially, the renewable energy resources are only considered to form the possible combinations with storage modules. Then the optimization is performed. Subsequently, non-renewable energy generators such as DG are added with these combinations if the previous ones fail to meet the objective. After that the optimization is again performed for the modified combinations. The environmental impact assessment through LCA and economic risk assessment of these combinations using MCS are performed to obtain the intermediate feasible solutions. In this study, SimaPro® is used for the LCA. The primary economic factor, i.e., COE of the energy combinations is affected due to the variations in several economic input parameters such as capital expenditure (CAPEX) and operational expenditure (OPEX) of the components, fuel cost, discount rate and the interest rate in addition to the energy produced from these combinations. If a single solution emerges as the best for all three criteria simultaneously, then it is considered as the best solution. Otherwise, if different combinations emerge as the best options for respective criteria, then MCDM approach is used to decide the finally acceptable optimum solution.

7.2.3.1 HOMER® analysis:

The detailed working principle of HOMER® is shown in discussed in Chapter 5, in "Sec. 5.3.3.1: HOMER® methodology" (Ramesh & Saini, 2020). The detailed way of obtaining the optimal solution is shown in Fig. 7.5.

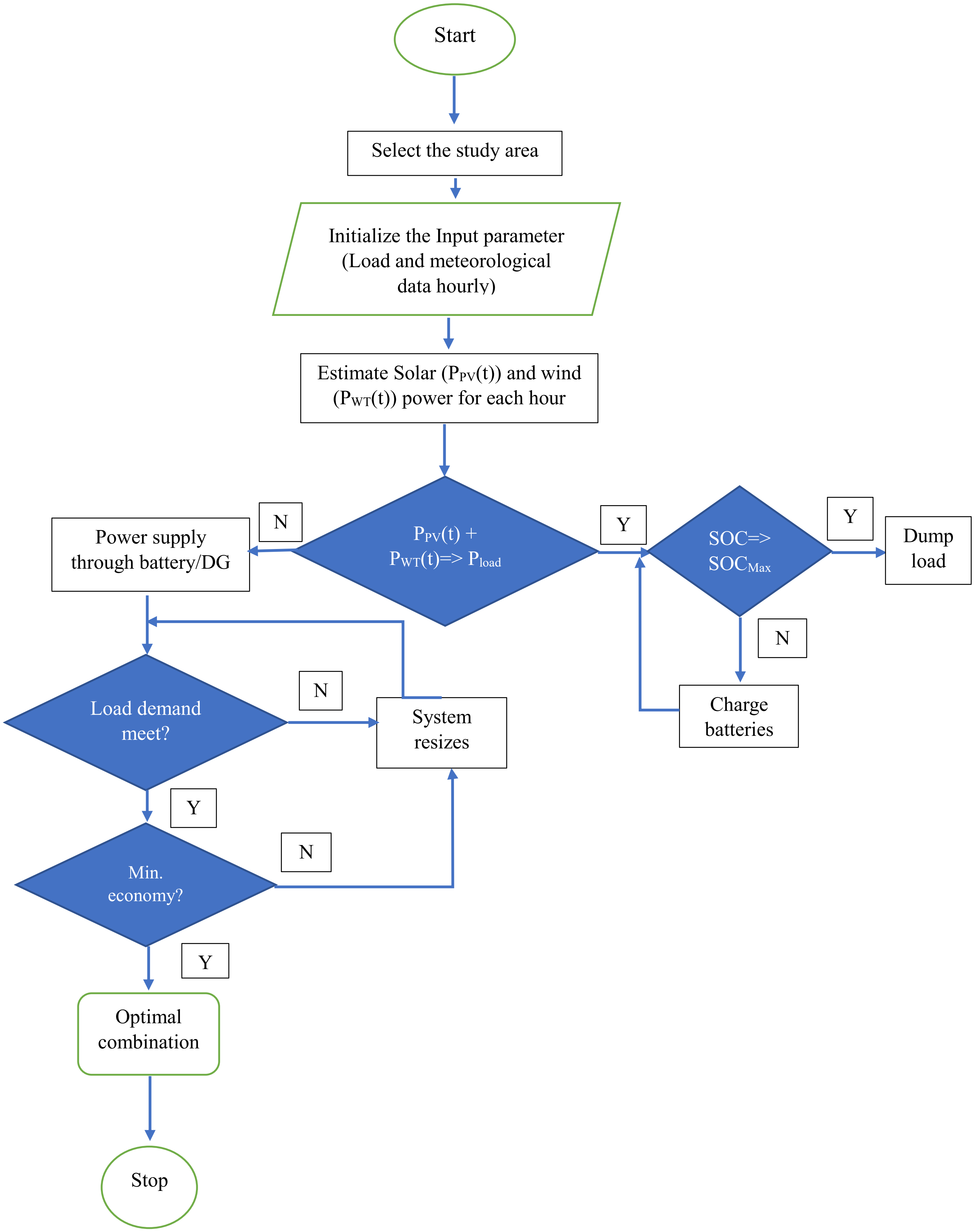


Fig. 7.5: Flowchart of optimal sizing determination

Figure 7.5 explains the process of determining an optimal energy combination. Firstly, the single renewable energy systems are evaluated. After satisfying the required load demand, the surplus electricity is used to charge the battery if required. The storage module is used when the renewable energy generators are unable to meet the demand. If the only renewable combinations supported by storage devices failed to meet the required load demand during the peak load period (UL), then the DG module is attached with that combination. The reliability of the combination was improved by meeting the required energy demand through overcoming the UL. The UL is discussed in Eq. i, Sec. 1.i of Table A.2 (SI) (Ali et al., 2021).

The optimization was performed to obtain the optimal capacity and the least cost of the system at which it could satisfy the energy demand. The optimization process performed in HOMER®. The detailed working principle of HOMER® is shown in discussed in Chapter 5, in "Sec. 5.3.3.1: HOMER® methodology" (Ramesh & Saini, 2020). The major economic evaluation metrics for the proposed energy combinations, analysed by the HOMER® is COE. The COE is shown in Eq. i, in Table A.2, Sec. 2 of SI.

Through this analysis renewable energy share (RES) in total electricity produced by the combination. The estimation of RES is discussed in Eq. i, Table A.2, Sec. 3.i of SI.

The objective of the optimization in this study is to provide the energy combination with the least COE for the study area that met the required load demand. The objective function of this study is shown in Eq. 7.1.

$$C_{obj} = f\ (minimize\ COE, UL) \tag{7.1}$$

7.2.3.2 Monte Carlo Simulation for risk assessment:

Risk analysis is the deep economic concept under the finance theory domain. It is an essential concept in the capital market. This concept is used by the economic analysts to estimate the share price of the companies, to assess the project risk, and to calculate the return of investment in future (Rout et al., 2018). Generally single point and three-point estimation are the two classical approaches. Though these two methods were used in risk analysis previously, these methods are not realistic and unable to report the uncertainties perfectly. Hence, the probabilistic distribution approach is preferred for risk analysis (Rout et al., 2018). This method provides the full range of the possible outputs along with their possibility of occurrences. MCS is one of the extensively used probability distribution approaches that provides the stable result of the forecasted economy.

Risk analysis is used to find, allocate and assess the financial risk on ROI in decentralized energy projects. The objective of risk analysis is to give attention to potential input parameters that could have the impact on cash-flow of the project, perform qualitative and quantitative evaluation of the possible effects of input parameters on project earnings and also on its viability, and lastly reduce the economic risk of the project by taking appropriate measures. From the investors' point of view, the aim of risk analysis is to provide assurance that the project should be able to return an investment in a base-case scenario which is associated with the uncertainties and incorporated risk. In this respect, analysing the uncertainties related to the COE of the energy system that provides an idea of the project attractiveness to investors are subject to risk evaluation (Arnold & Yildiz, 2015).

MCS is not extensively used to analyse the risk of the renewable energy infrastructure, because it demands extensive data processing and the selection of probability density functions for random input parameters. In this study, the MCS is used to evaluate how the uncertainties of the input parameters are affecting the COE of the energy system and how much the system is economically stable. The term economically stable defines how the project will return on the investment at an estimated period. Hence, economic risk analysis is required, specifically for investment in new technology implementations. The uncertainties of essential input parameters such as capital cost, operational cost, discount rate, lifetime of the project, fuel cost, renewable energy and diesel generator energy that are considered in COE analysis are analysed in this study.

The working methodology of the MCS is shown in Fig. 7.6 (Uwineza et al., 2021).

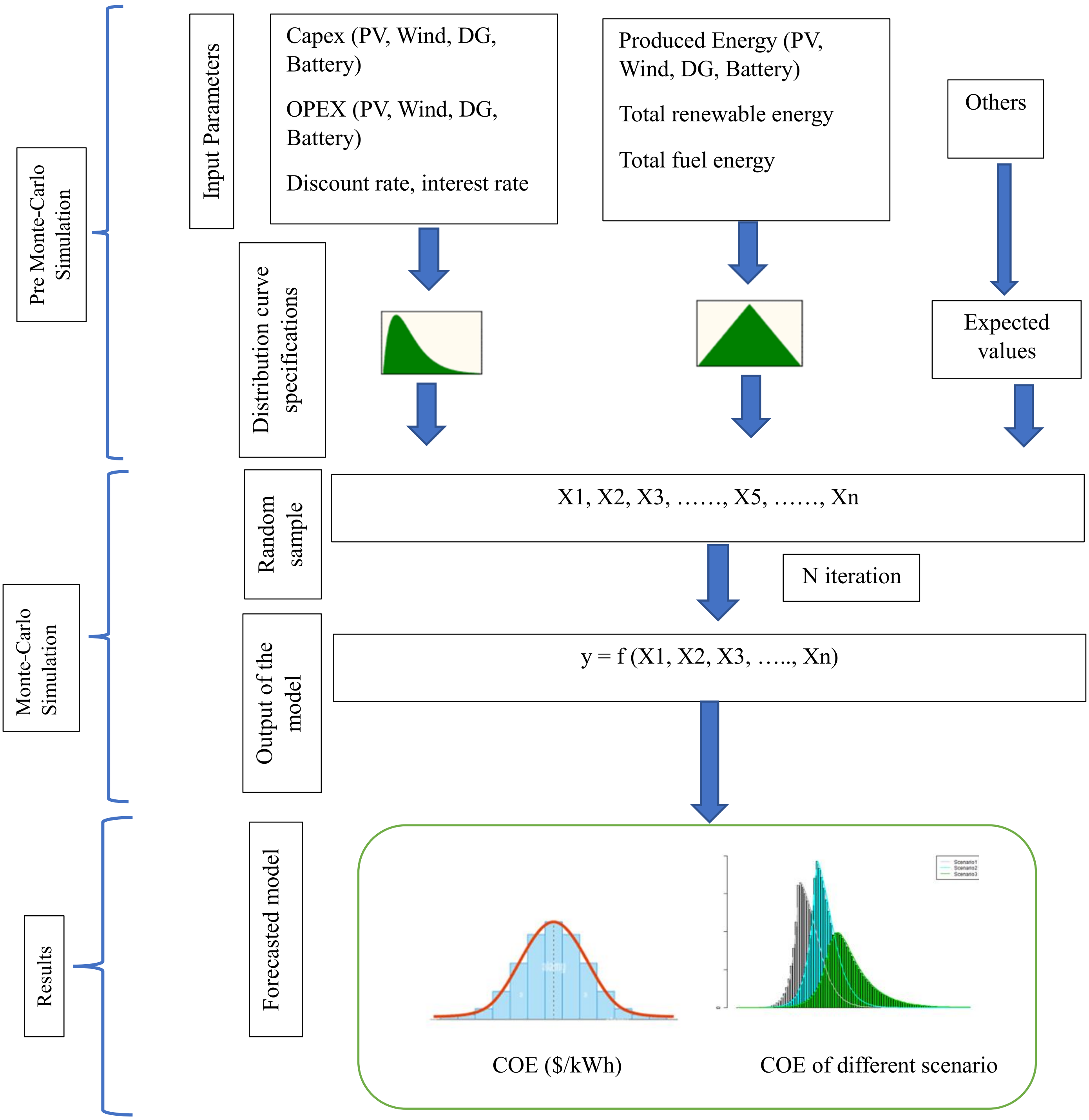


Fig. 7.6: Monte Carlo Simulation method working principle (Uwineza et al., 2021)

According to the figure, firstly, the probability range of the considered input parameters are to be estimated, and the probability distribution function is to construct from the literature survey. The mean and the variance of the sample data are calculated using Eqs 7.2 and 7.3 respectively (Uwineza et al., 2021).

$$\mu = \frac{\sum_{i=1}^{n} X_i}{n} \quad (7.2)$$

$$S_n^2 = \frac{\sum_{i=1}^{n} X_i}{n} - \mu^2 \quad (7.3)$$

Where μ is the mean of the sample, X_i is the input variable, S_n^2 is the variance of the statistics and n is the sample size.

In the next study, input parameters are studied and the goodness of fit test is performed to evaluate the statistical analysis. This analysis helped to comprehend how the uncertainty of different parameters affected the financial performance factor, especially COE of the energy combination project. In this analysis, the input parameters are decided for performing the economic risk analysis. Bayesian information criteria (BIC), the famous curve fitting test, is used to determine the best fit distribution of the input parameters. The BIC is calculated using Eq. 7.4 (Uwineza et al., 2021).

$$BIC = 2 \times \ln(l) + k\ln(n) \quad (7.4)$$

Where sample size is n, k is the total number of free constraints, and l is the fn. of likelihood. The BIC values of each probability distribution function are calculated using this model and the lower value of the BIC is considered as the best fit distribution value. The values and probability distribution of the above-mentioned input parameters are shown in Table 7.2.

Table 7.2: Input parameters distribution function (Uwineza et al., 2021)

	Min	**Max**	**Mean**	**Standard deviation**	**Simulation**
PV					
CAPEX (PV)	425.25	809.55	617.4		Exponential
OPEX (PV)	10.63	20.23	15.43		Exponential
Wind					
CAPEX (Wind)	762	1602	1182		Exponential
OPEX (Wind)	12	60	36		Exponential
DG					
CAPEX (DG)	502.5	997.5	750	247.5	Log-normal
OPEX (DG)	2.2	6.1	4.15	1.95	Normal
Battery					
CAPEX (Battery)	67.83	271.42	169.625	101.795	Exponential
OPEX (Battery)	6	24	15	9	Triangular
Fuel cost ($/Litre)	0.4	2	1.2	0.8	Normal

Discount rate (%)	4	16	10	6	Normal
Solar radiation (kW·h/m^2/day)	6	7	6.5	0.5	Normal
Wind speed	5	8	6.5	1.5	Weibull

The economic risk of the model is analysed using the considered input values. This risk analysis is performed on the basis of the MCS model shown in Eq. 7.7 (Uwineza et al., 2021).

$$\begin{bmatrix} COE_1 \\ \cdot \\ \cdot \\ \cdot \\ COE_j \end{bmatrix} = \begin{bmatrix} Capital\ cost_1 & Operation\ cost_1 & i_1 & RE_1 & DE_1 & fuel\ cost_1 & dis\ rate_1 & R_{Pro1} \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ Capital\ cost_j & Operation\ cost_j & i_j & RE_j & DE_j & fuel\ cost_j & dis\ rate_j & R_{Proj} \end{bmatrix} \quad (7.7)$$

7.2.3.3 LCA approach:

The environmental impact of the energy systems has been performed in this analysis. The analysis is carried out by a LCA approach. The SimaPro® version 9 is used to carry out the LCA analysis. The other details of this method and the data inventory considered for this analysis are discussed in Chapter 6, "Sec. 6.4.4.3: LCA methodology"

7.2.3.4 MCDM technique:

The MCDM approach is used to explore the final optimum solution in this integrated method with possible weightages to three criteria: cost, investment risk and environmental degradation. Firstly, this approach is used to select the energy combination with feasible environmental impact, analysed through the LCA process. The process is again performed to select the optimal energy combination. In this step the solution obtained through the economic optimization, risk analysis and the environmental impact are compared. In both stages of analyses the weightages of the three criteria had been varied within certain ranges to examine the reliability of the obtained result. The TOPSIS- MCDM technique is used in this analysis. The algorithm is discussed in Chapter 5, in "Sec. 5.3.3.2.1: TOPSIS-MCDM algorithm".

7.2.4 Load analysis:

The load demand analysis is considered as the basic input parameter for techno-economic optimization and the load of the considered study area is determined on the basis of mathematical processes discussed in reference (Ramesh & Saini, 2020). Based on available data the load demand of the area is estimated (Harish et al., 2022; Kumar et al., 2013). The load of the area is determined for two seasons (summer and winter. During summer the daily load is 491.7 kW·h and during winter the daily load is reduced to 455.35 kW·h. The average load is

474.09 kW·h/day and the peak load is 52.15 kW. The load factor is 0.38. The load distribution curve is shown in Fig. 7.7.

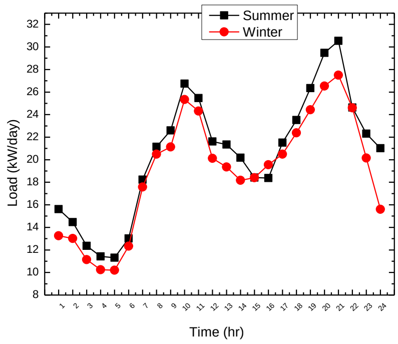


Fig. 7.7: Load flow graph (Harish et al., 2022; Kumar et al., 2013)

7.3 Results and discussions:

This study is aimed to find an optimum capacity of the decentralized hybrid energy system for best possible economy and resource utilization to meet the local demand. The risk assessment on ROI is also performed in this study from investors' perspective. The details of the analysis results are discussed below.

7.3.1 Energy combination selection:

The decided objective is to satisfy the local load demand of the considered location. To do so firstly, the study analyses only renewable energy resources combined with storage modules such as PV-wind-Battery, PV-Battery and Wind-Battery. In this study Li-ion Battery system is considered. The evaluation result is shown in Fig. 7.8. The figure shows the normalized value of the result to reduce the redundancy of the analysis.

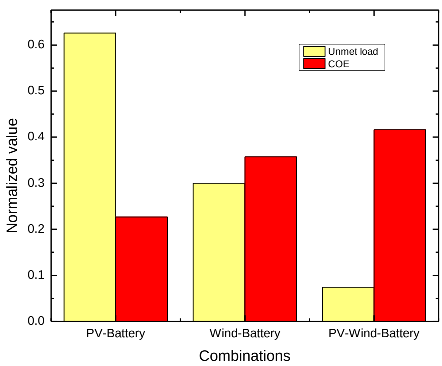


Fig. 7.8: Only renewable energy combinations for UL and COE

Figure 7.8 shows that only renewable resource-based combinations are unable to meet the estimated load. For these combinations significant ULs are present. The UL decreases in hybrid combinations using two renewable resources (PV-wind-Battery) than that using single renewable resources. According to the analysis it is noted that during the peak load demand energy combinations fail to meet the required demand. The COE is high in PV-wind-battery-based hybrid solution as compared to other options. The capacities of the components in different combinations are shown in Table 7.3.

Table 7.3: Capacities of the components for only renewable and DG based reference systems

Combinations	**PV (kW)**	**Wind (kW)**	**Li-ion**	**DG**	**COE ($/kW·h)**	**Unmet load (%)**
PV-Battery	321		578	0	0.22675	0.62579
Wind-Battery		144	802	0	0.35726	0.29996
PV-wind-Battery	80	38	451	0	0.41599	0.07425
DG-Battery			222	58	0.51	0

The table shows the optimum capacities of the energy modules for the best possible economy and resource utilization. The increase of size may assuredly meet the load demand but it will simultaneously increase the COE value of the system. It may exceed the COE of the currently existing reference value for only DG based systems.

Thus, the best possible option is to add the DG system with the renewable based systems to meet the UL during peak loads without increasing the module's capacity for a better economic solution. The use of DG is restricted and it is only used during the peak load demand period. Three different hybrid energy combinations (PV-DG-Battery, wind-DG-Battery, PV-wind-DG-Battery systems) are developed and considered for techno-economic optimization. The DG-Battery system is considered as a reference case and compared along with these three combinations. The COE is considered as the major economic performance factor in this study to select the economically optimal solution. The analysis result of the combinations is shown in Table 7.4. These capacities of the energy modules are also shown in this table.

Table 7.4: Techno-economic analysis result

Combination number	**Scenario**	**COE ($/kW·h)**	**PV**	**Wind**	**Battery**	**DG**
1st combination	DG-Battery	0.51	-	-	222	58
2nd combination	PV-DG-Batt	0.21	214	-	473	46

3rd combination	Wind-DG-Batt	0.262	-	154	547	42
4th combination	PV- wind-DG-Batt	0.156	85.1	33	399	30

According to the table the COE is maximum for DG-Battery system ($0.51/kW·h) and minimum for PV-wind-DG-Battery ($0.156/kW·h). Others are the Wind-DG- Battery system ($0.262/kW·h) and the PV-DG-Battery system ($0.21/kW·h). The analysis result shows that the maximum percentage of energy is contributed by the wind module in PV-wind-DG-Battery combination. The energy share of wind modules for PV-wind-Battery-DG combination is 59.9% and the share of solar modules is 40%. The rest of the total energy is met by the battery and DG system. At the peak load period only to avoid any power cut, the DG set is considered to be essential. The renewable fraction of this combination is 99.8%. Hence, the CO_2 emission from this module is lower than other energy combinations (approximately 389 kg/year). The emission is maximum for the DG-Battery system. The financial risk analysis on ROI for obtaining a stable energy solution is performed for the considered combinations subsequently.

7.3.2 Economic risk analysis:

The risk on investment for new technologies must be anticipated and as low as possible for attracting more investors in this field. This study performed economic risk analysis of the energy combinations using MCS to provide the estimated economic uncertainty for different alternative energy combinations to meet the demand. The major economic performance factor is the COE. Possible variations in input economic parameters, mainly capital and operation costs of the component modules and developed energy from different energy generators have impacts on the COE of a combination of modules. For a favourable investment condition, risk assessment of COE of the systems is recommended. The MCS approach is the best possible method to analyse the impact of these variations on the COE and provides economically stable energy combinations. After several successful iterations the results are obtained through MCS based on the data obtained from the previous techno-economic optimization. The higher the standard deviation of a combination, the higher is the economic risk. It is directly related to the energy generation uncertainty. Figure 7.9 shows the distribution of COE of different combinations.

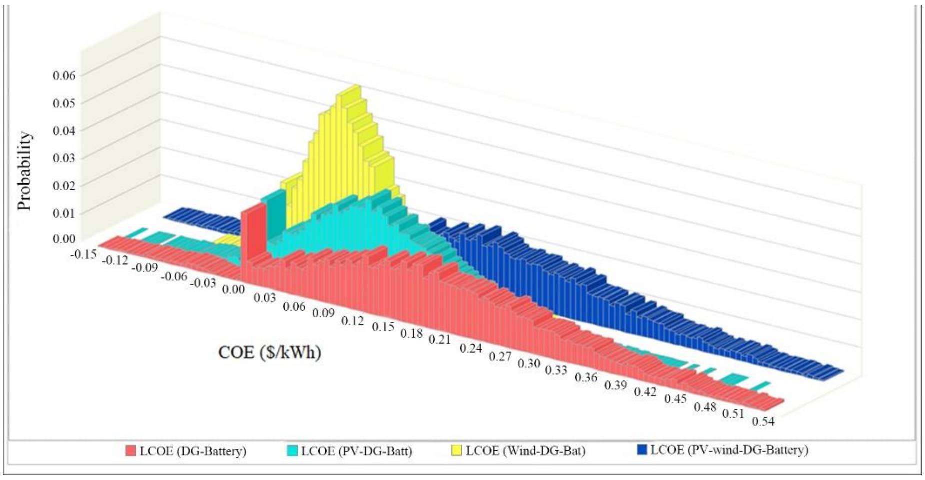


Fig. 7.9: Histograms of COE distribution for different energy combinations

Figure 7.9 shows that the COE of the Wind-DG-Battery model is being skewed on the left-hand side on the graph. The certainty is more in wind-DG-Battery systems (99.6%) followed by PV-DG-Battery (99.3%) and PV-wind-DG-Battery (88%) combinations. The deviation is maximum in DG-Battery system (0.12) followed by PV-wind-DG-Battery (0.119) system and PV-DG-Battery systems (0.07). The wind-DG-Battery module is more competitive as compared to other combinations. The DG-Battery and PV-wind-DG-Battery modules have the long "tails" on the right-hand side of the graph. It is because to the uncertainty is associated with the discount rate and the operation and reinvestment cost of the storage module followed by the DG system. Figure 7.10 shows the impact of different input parameters on the system's COE variation. According to the figure the impact of the discount rate is maximum on COE of different energy combinations followed by storage and DG operation costs.

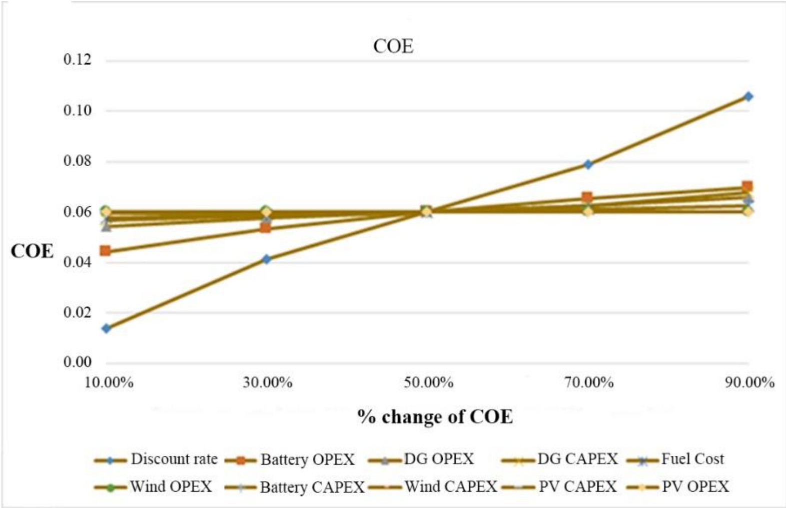


Fig. 7.10: Impact of input parameters on COE

The mean and the standard deviation of the combinations is shown in Table 7.5.

Table 7.5: Results of statistical analysis of economic risk assessment

Statistic	COE (DG-Battery)	COE (PV-DG-Battery)	COE (Wind-DG-Battery)	COE (PV-wind-DG-Battery)
Trials	10,000	10,000	10,000	10,000
Base Case	'---	'---	'---	'---
Mean	0.19	0.11	0.06	0.19
Median	0.18	0.11	0.06	0.18
Mode	'---	'---	'---	'---
Standard Deviation	0.12	0.07	0.04	0.12
Variance	0.01	0.01	0.00	0.01
Skewness	0.4091	0.4076	0.4083	0.4069
Kurtosis	3.63	3.63	3.63	3.63
Coeff. of Variation	0.6416	0.6414	0.6415	0.6413
Minimum	-0.23	-0.14	-0.07	-0.24
Maximum	0.82	0.50	0.26	0.83
Mean Std. Error	0.00	0.00	0.00	0.00

Table 7.5 shows that the standard deviation is minimum in wind-DG-Battery system (0.04) followed by PV-DG-Battery (0.07). In PV-wind-DG-Battery and DG-Battery systems the standard deviation is maximum, i.e., about 0.12. The variance is 0 for the wind-DG-Battery system and 0.01 for other combinations. According to the MCS, the high standard deviation reflects more economic uncertainty the analysis showed that the combination of PV-wind-DG-Battery with minimum COE ($0.156/kW·h) has more economic risk. The impact of variations of input parameters is higher on this combination. The least risk is associated with the combination of wind-DG-Battery systems whose COE is also the second highest (COE-

\$0.26/kW·h) among the considered combinations PV-DG-Battery system. In the next step the environmental impacts of these combinations are estimated through LCA.

7.3.3 Environmental impact analysis:

The CO_2 emission is minimum in PV-wind-DG-Battery systems. However, along with the emission analysis detailed environmental impact assessment is carried out in this study The LCA method is used to evaluate the environmental impact of different combinations. The end-point analysis of the LCA approach is performed in this study. The 18 subfactors obtained in mid-point analysis of the LCA approach are summarized in this end-point analysis. In the end-point analysis, mainly three categories are obtained such as human health, ecosystem and resources scarcity. The analysis results are shown in Fig. 7.11.

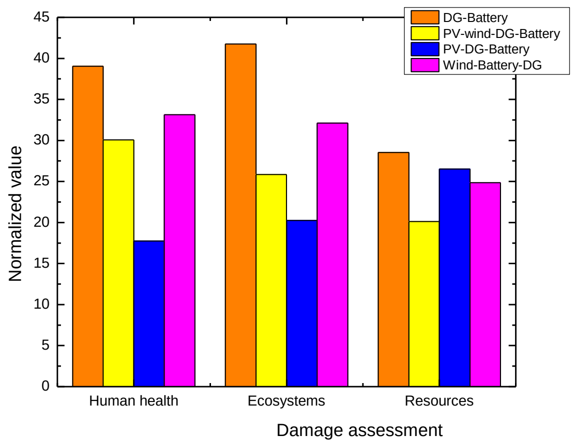


Fig. 7.11: Environmental impact end-point analysis

The data of the analysis is also shown in Table 7.6.

Table 7.6: End-point analysis data

Damage category	DG-Battery	PV-Wind-DG-Battery	PV-DG-Battery	Wind-Battery-DG
Human health	59769.24399	46986.79548	27740.03396	51795.83287
Ecosystems	54.82294924	29.50386856	23.10924424	36.6489143
Resources	485421744.5	342102642.1	450957067.5	422714460.4

The results show that the PV-DG-Battery system has a lower impact on human health (2270.03) and ecosystem category (23.11). However, for the resource scarcity factor the PV-wind-DG-Battery module has lower impact as compared to the other combinations. The DG-Battery combination has the highest environmental impact followed by wind-DG-Battery systems. Therefore, no combination is absolutely optimal from the viewpoint of environmental impact. Hence to find the optimum environmental solution the MCDM approach is introduced. Four alternatives (DG-Battery, PV-Battery-DG, wind-Battery-DG, PV-wind-DG-Battery) and three criteria (human health, ecosystem and resources scarcity) are considered for this MCDM process. The TOPSIS-MCDM algorithm is considered in this study. Primarily equal weightages have been given to the criteria. Then the weights are varied within the decided range to evaluate the reliability of the obtained solutions. These weights are placed under six categories. Approximately 25 case studies are considered in this analysis with different weights of the criteria. The weight variations of the criteria are shown in Table 7.7. The MCDM analysis result is shown in Table 7.8.

Table 7.7: Weight variations of the criteria

case	Equal priority	Priority given to human health							Priority given to ecosystem					Priority given to resource scarcity						Both human health and ecosystem		Both ecosystem and resource scarcity		Both human health and resource scarcity	
	Case 0	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case 9	Case 10	Case 11	Case 12	Case 13	Case 14	Case 15	Case 16	Case 17	Case 18	Case 19	Case 20	Case 21	Case 22	Case 23	**Case 24**
Weightage																									
W1	0.333	0.4	0.6	0.6	0.7	0.7	0.8	0.3	0.1	0.3	0.2	0.1	0.1	0.3	0.1	0.3	0.2	0.1	0.1	0.5	0.4	0.1	0.1	0.4	**0.5**
W2	0.333	0.3	0.3	0.1	0.2	0.1	0.1	0.4	0.6	0.6	0.7	0.7	0.8	0.3	0.3	0.1	0.1	0.2	0.1	0.4	0.5	0.5	0.4	0.1	**0.1**
W3	0.333	0.3	0.1	0.3	0.1	0.2	0.1	0.3	0.3	0.1	0.1	0.2	0.1	0.4	0.6	0.6	0.7	0.7	0.8	0.1	0.1	0.4	0.5	0.5	**0.4**

Table 7.8: Results of MCDM analysis for feasible environmental impacts of different combinations

	Rank (DG-Battery)	Rank (PV-wind-DG-Battery)	Rank (PV-DG-Battery)	Rank (Wind-DG-Battery)
Case 0	4	2	1	3
Case 1	4	2	1	3
Case 2	4	2	1	3
Case 3	4	2	1	3
Case 4	4	2	1	3
Case 5	4	2	3	1
Case 6	4	2	1	3
Case 7	4	2	1	3
Case 8	4	2	1	3
Case 9	4	2	1	3
Case 10	4	2	1	3
Case 11	4	2	1	3
Case 12	4	2	1	3
Case 13	4	2	1	3
Case 14	4	2	1	3
Case 15	4	2	1	2
Case 16	4	1	2	3
Case 17	4	1	2	3
Case 18	4	3	2	1
Case 19	4	2	1	3
Case 20	4	2	1	3
Case 21	4	2	1	3
Case 22	4	2	1	3
Case 23	2	1	2	3
Case 24	2	1	2	3

In environmental impact assessment the MCDM results show that the PV-DG-Battery module is the feasible energy combination. Almost for all cases this combination has the highest performance score which makes the rank of this combination relatively higher. If the priority of resource scarcity (case 16, 17 and 18) and the priority for both human health and resource scarcity becomes high (Case 23 and 24) then only the performance score of PV-wind-DG-Battery is higher. It verifies that PV-DG-Battery may be accepted as more environment friendly as compared to other combinations.

7.3.4 MCDM approach for the final optimum solution:

Independent assessment of economy, technical efficiency, risk on investment and environmental impact are discussed above in the sub-sections 3.1-3.3. It is noted that the best option for each of these criteria converges to different combinations of energy resources. The result shows that the PV-wind-DG-Battery combination is economic but less environment friendly with high economic risk. PV-DG-Battery model is environment friendly but COE and the economic risk of this combination is not the minimum. Finally, according to the economic risk assessment wind-DG-Battery model is the best combination but COE and environmental impact of that combination is relatively higher. Hence, the final optimum option must be obtained through MCDM. The TOPSIS-MCDM is used to select the energy combination with a feasible combination of cost, economic risk and environmental impact. However, the weights of these three criteria for MCDM approach must be in line with the defined objective of the optimum solution. The MCDM analysis is performed by varying the weights of the criteria within the considered ranges to examine the best acceptability out of different solutions. Initially equal weights are assigned for each criterion and subsequently it is varied within a certain range (0.1-0.8). The weights are placed under six different categories. The different weights are shown in Table 7.9. The analysis is performed based on those weights and the result of the analysis is shown in Table 7.10.

Table 7.9: Different weights of the three criteria

case	Equal Priority	Priority given to cost							Priority given to reliability					Priority given to environmental sustainability						Both cost and reliability		Both reliability and environmental sustainability		Both cost and environmental sustainability	
Weightage	Case 0	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7	Case 8	Case 9	Case 10	Case 11	Case 12	Case 13	Case 14	Case 15	Case 16	Case 17	Case 18	Case 19	Case 20	Case 21	Case 22	Case 23	Case 24
W1	0.333	0.4	0.6	0.6	0.7	0.7	0.8	0.3	0.1	0.3	0.2	0.1	0.1	0.3	0.1	0.3	0.2	0.1	0.1	0.5	0.4	0.1	0.1	0.4	0.5
W2	0.333	0.3	0.3	0.1	0.2	0.1	0.1	0.4	0.6	0.6	0.7	0.7	0.8	0.3	0.3	0.1	0.1	0.2	0.1	0.4	0.5	0.5	0.4	0.1	0.1
W3	0.333	0.3	0.1	0.3	0.1	0.2	0.1	0.3	0.3	0.1	0.1	0.2	0.1	0.4	0.6	0.6	0.7	0.7	0.8	0.1	0.1	0.4	0.5	0.5	0.4

Table 7.10: MCDM result

Cases	Rank (PV-DG-Battery)	Rank (Wind-DG-Battery)	Rank (PV-wind-DG-Battery)
Case 0	1	2	3
Case 1	1	2	3
Case 2	1	2	3
Case 3	1	3	2
Case 4	2	3	1
Case 5	2	3	1
Case 6	2	3	1
Case 7	1	2	3
Case 8	1	2	3
Case 9	1	2	3
Case 10	2	1	3
Case 11	2	1	3
Case 12	2	1	3
Case 13	1	3	2
Case 14	1	3	2
Case 15	1	3	2
Case 16	2	1	3
Case 17	2	1	3
Case 18	2	1	3
Case 19	1	2	3
Case 20	1	2	3
Case 21	1	2	3
Case 22	1	2	3
Case 23	1	3	2
Case 24	1	3	2

For this MCDM study the 25 cases are divided into seven categories. When the weights of these categories are in medium range then the feasible energy combination is PV-DG-Battery. If the weights of the cost criteria increases (above 0.7) then the rankings of different combinations change. The analysis shows that in this period the PV-wind-DG-Battery combination obtains the high-performance score and this combination gets the top rank. Similarly, under the reliability category if the weightage value increases to 0.7 then the ranking shifts. If the weightage is high for the environmental impact (above 0.7) then the ranking of the alternatives is changing. If the weightages for two criteria are varied then also the ranking is constant. The rankings of the alternative combinations are nearly constant for maximum variations and PV-DG-Battery combination is found to be the best energy combination. By varying the weights of the criteria, it is validated that the PV-DG-Battery combination remains a feasible solution with moderate cost, economic risk and environmental impact. Hence, the total integrated methodology of the study shows that PV-DG-Battery combination may be accepted as the final optimum energy solution for the location to meet the load demand of the study area at feasible economy (COE-\$0.21/kW·h) and financial risk (standard deviation-0.07). The combination is also environmentally optimum as compared to other combinations.

7.4 Summary of the Chapter:

This study aims to obtain a techno-economically optimal combination with negligible investment risk and environmentally benign energy combination to meet the required load. Finally, the MCDM approach is used to decide an optimum solution from the output of three independent analyses (i.e., techno-economic, financial risk assessment and LCA). Different combinations of renewable power with DG and Battery are explored to meet the full load demands with cost assessments (i.e., COE) through techno-economic evaluation. The best option at this stage has emerged to be the PV-wind-DG-Battery system with a minimum COE of \$0.156/kW·h. In the next step, risk on investment for all these options due to different future uncertainties are assessed. These are represented by corresponding standard deviations of the MCS. The Wind-DG-Battery system has emerged as the best option with a minimum standard deviation of 0.04. Subsequently a comprehensive three criteria (human health, resource scarcity and ecosystem) LCA is done. PV-DG-Battery system has the least environmental impact as assessed by the LCA combined with MCDM. As these three solutions are different, MCDM is used to decide the final optimum solution. With a study of widely varying weights of these three criteria (cost, risk on investment and environmental impacts) in MCDM the recommended optimum solution for this village is PV-DG-Battery with a COE of \$0.21/kW·h and a standard deviation of the MCS of 0.07.

CHAPTER- 8

Comparative analysis of different storage and dispatch strategies

(***Das, S.**, Ray, A., De, S.* (2022): Comparative analysis of storage modules under different dispatch strategies for an optimum decentralized hybrid energy solution: a case study of a remote Indian village. **Clean Technology and Environmental Policy (Springer)** (**Published**). DOI: https://doi.org/10.1007/s10098-022-02330-0)

8.1 Objective of the work:

This study proposes a comparative analysis of the different storage technologies under different dispatch strategies to explore an optimum reliable distributed power supply at a minimum cost for a remote village of India. This comparative analysis provides the techno-economically optimal storage technology under reliable dispatch strategy. These results help to determine the optimum techno-economic energy solution to meet the local load demand. The sensitivity and reliability analyses are also carried out for the determined optimum energy combination with appropriate storage device under the selected dispatch strategy. The Loss of Power Supply Probability (LPSP) and Unmet Load (UL) methods are also used to evaluate the reliability of the uninterrupted power supply. Any excess electricity after meeting the load during operation due to varying load and intermittent renewable resources (without DG set operating) is considered as a dump load.

8.2 Study area details:

Analysis is done for a village of Bihar, an eastern state of India. The latitude and longitude of the selected study area is 26.440º N and 86.430º E (Census India, 2011). This remote village (400 households approximately) is still using DG and kerosene lamps for electricity and lighting (Census India, 2011, Central Electricity Authority, 2018). Renewable options including small hydropower from the local Tiljuga river and solar energy are considered for the HRES.

8.3 Materials and Methodology:

Five different storage modules (LA, Li-ion, VR, ZB Batteries, and PHES) are compared under two different dispatch strategies (LF and CC) (Das et al., 2021; Immendoerfer et al., 2017). This comparative study is performed on the basis of technical (efficiency, nominal capacity, annual throughput and minimum variation of the state of charge (SOC) of the storage module), economic (COE, NPC, and operation and maintenance (O&M) cost), and environmental (RF and carbon dioxide (CO_2) emission) factors. The analysis is performed in HOMER®. The The detailed working principle of HOMER® is shown in discussed in Chapter 5, in "Sec. 5.3.3.1: HOMER® methodology" (Ramesh & Saini, 2020). The conceived schematic model is shown in Fig. 8.1. The detailed technical description of the considered storage modules is given in Table 8.1. The simulation methodology is described in a flow chart of the algorithm used in Fig. 8.2.

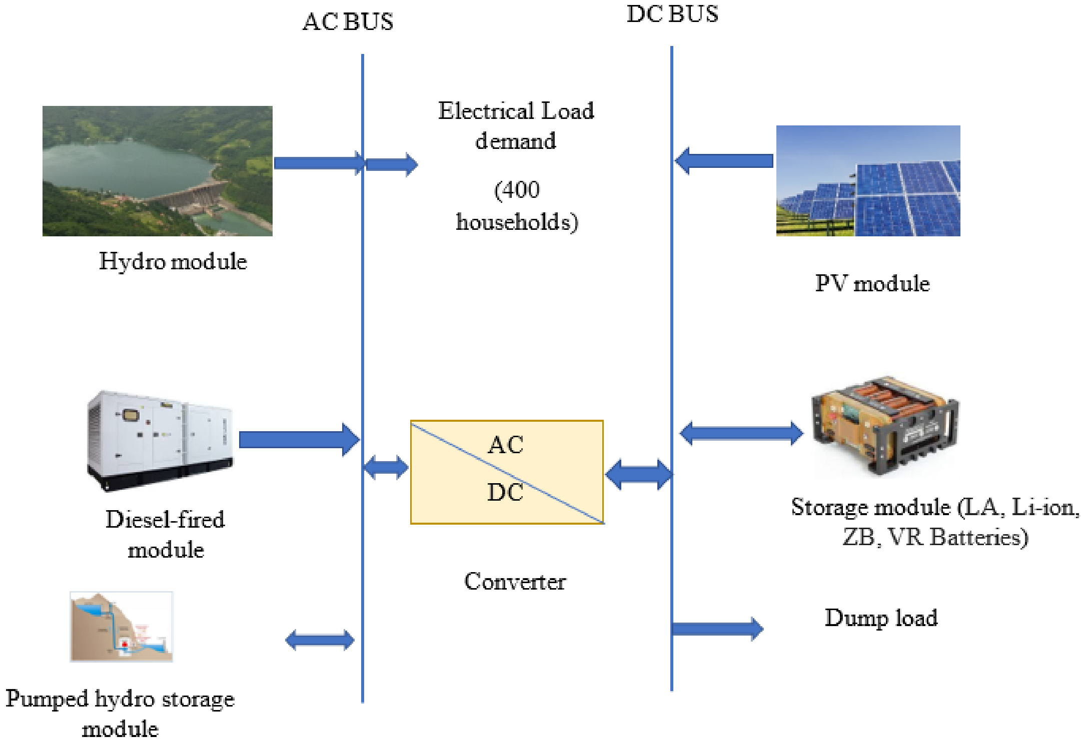


Fig. 8.1: Schematic of the energy system model

Table 8.1: Technical comparison of different storage systems (Das et al., 2019, Das et al. 2021, Das and Zaman, 2019, Das et al., 2017, HOMER, 2017, Testa et al., 2010, Barote et al., 2008, Immendoerfer et al. 2017):

Parameters	**Lead-Acid battery (LA)**	**Li-ion battery (Li-ion)**	**Hybrid flow (Zinc-Bromide) battery (Z-B)**	**Redox flow (Vanadium-redox battery) (V-R)**	**Pumped hydro**
Storage mechanisms	Electrochemical	Electrochemical	Electrochemical alloy	Electrochemical Alloy	Mechanical
Lifetime (year)	3-12	5-15	5-10	>20	50
Self-Discharge rate	Very Low	Low	Negligible	Negligible	Negligible
Energy density (Wh/Kg)	30	100-200	30-60	100-200	-
Efficiency (%)	70-80	80-95	80-85	75-80	65-80
Duration	Moderate	Moderate	Moderate	Moderate	Long-term
Environmental issues	Problem of disposal after use	Problem of disposal after use	Problem of disposal after use	Problem of disposal after use	Damages the natural environment

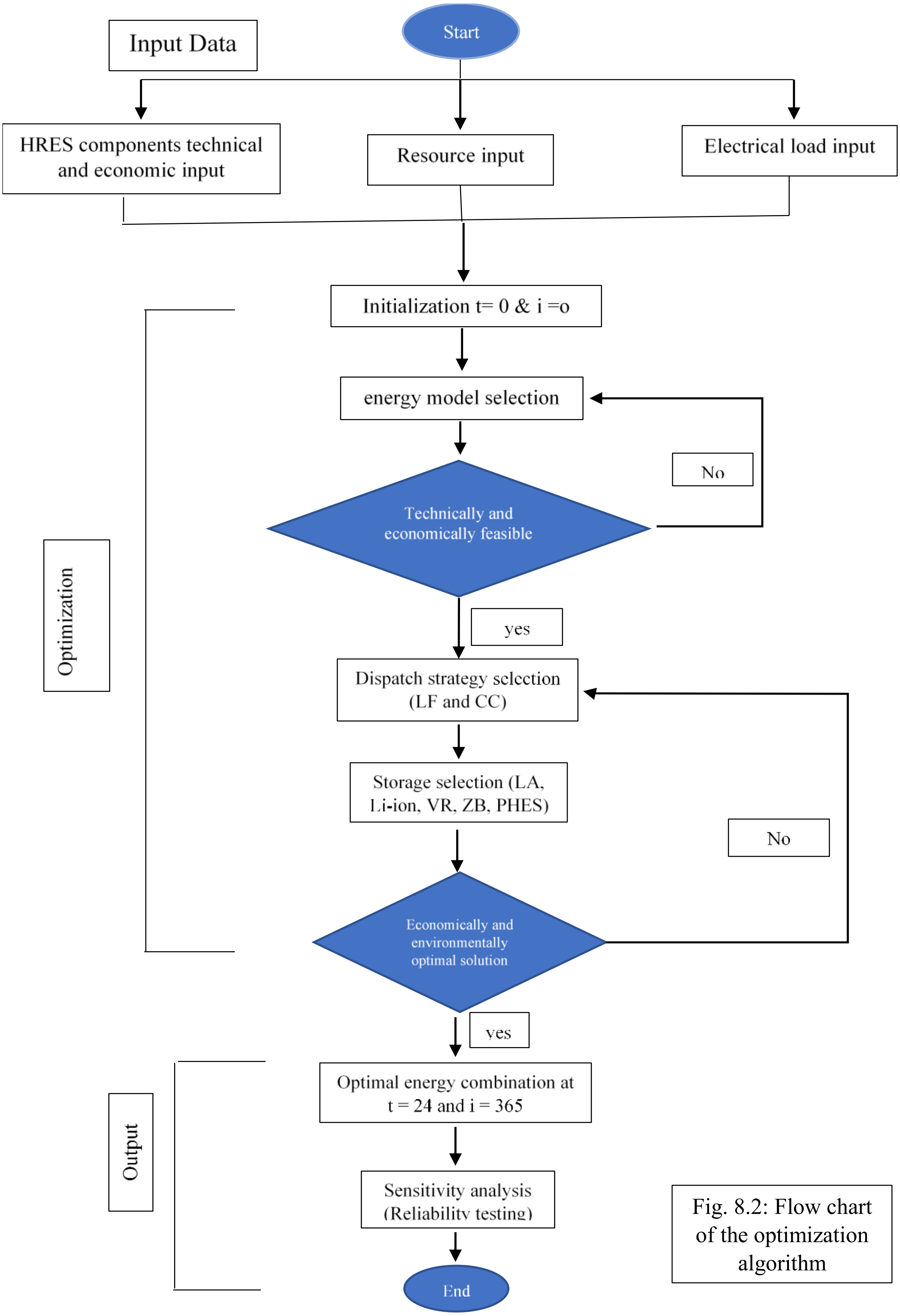


Fig. 8.2: Flow chart of the optimization algorithm

8.3.1 Input sources for analysis:

8.3.1.1 Load analysis:

During the summer season, the estimated energy is 427.560 kWh/day. During monsoon, this load is 381.610 kWh/day and during winter, the load demand reduces to 357.240 kWh/day. The yearly mean energy requirement is approximately 388.800 kWh/day (Government of India & Government of Karnataka, 2014). The mathematical analysis shows that the maximum load and the mean load values are 41.990 kW and 17.820 kW respectively. The daily average load data of the considered seasons is shown in Fig. 8.3.

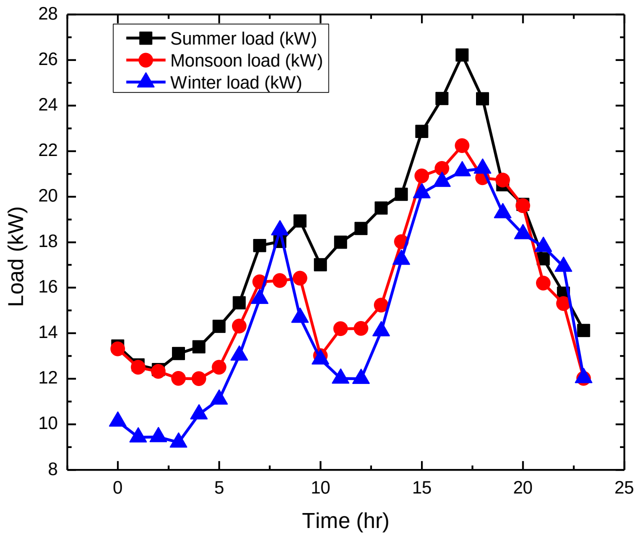


Fig. 8.3: Daily load distribution (Census India, 2011, Government of India & Government of Karnataka, 2014)

8.3.1.2 Energy sources and components modeling:

8.3.1.2.1 Photovoltaic (PV) modules modelling:

The output power of the PV module is discussed in equations shown in Table A. 1, Sl. No.: 1, Eqs. i-iii (Babatunde et al., 2022; Emad et al., 2021; Mandal et al., 2018) in Supplementary Index (SI).

The solar irradiance and ambient temperature data of the study area are collected from the NASA weather report (NASA, 2020). Figure 8.4 shows the yearly solar irradiance and clearness index. The daily radiation level is approximately 6.179 kWh/m^2/day and temperature are approximately 28°C.

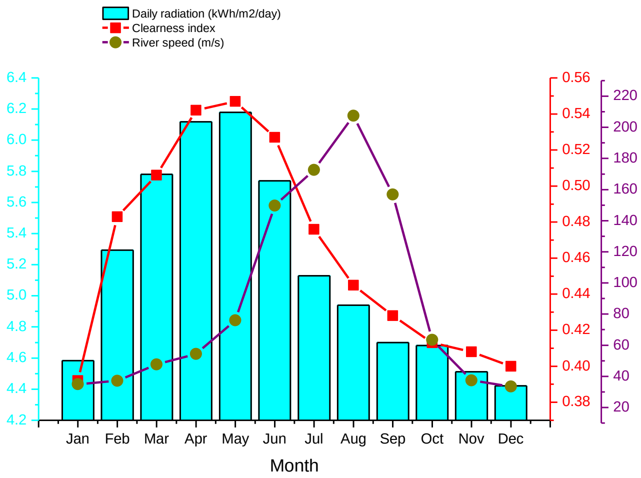


Fig. 8.4: Energy resources data (NASA, 2020)

In this analysis, 1kW solar modules is considered (Homer Energy, 2019). Technical details are provided in Table 8.2.

Table 8.2: Techno-economic specifications of components (Arévalo et al., 2020, Das et al., 2019, Das and Al-Abdeli, 2017, HOMER, 2017, Homer Energy, 2019, Mandal et al., 2018, Khalid et al., 2017):

Hybrid system's modules	Initial investment ($)	Replacement cost ($/kW)	O&M cost ($/kW)	Technical aspect
PV module	2,500/kW	0	10/year	1 kW, lifetime- 25 years
Hydro module	14,000/kW	4,000	255/year	40 kW, lifetime – 15 years
Diesel generator	470/kW	396	0.030/h	48kW, 50Hz, lifetime-1,500h
Inverter	800	750	8/year	1kW, lifetime-15 years
Lead acid (LA) battery	2,060	1,160	10/year	6V
Lithium-ion (Li-ion) battery	6,500	6,000	None	12kWh
Vanadium redox (VR) battery	11,000	4,600	1,000/year	Continuous charging and discharging capacity- 10kW, Nominal capacity – 100 kWh
Zinc Bromide (ZB) battery	400	400	10/year	1kWh,600V
Pumped hydro energy storage (PHES)	1,000	1,000	100/year	345kWh,240V

8.3.1.2.2 Hydropower component modeling:

The output power of hydro module is discussed in equation shown in Table A. 1, Sl. No.: 3, Eq. i (Arévalo et al., 2020) in SI.

In this study, the rated capacity of hydropower is assumed as 40kW (Arévalo et al., 2020). Detailed description is provided in Table 8.2.

8.3.1.2.3 Storage system modeling:

The equations of storage systems are discussed in Table A. 1, Sl. No.: 4, Eqs. i-v in SI (Baneshi & Hadianfard, 2016). Storage modules' techno-economic descriptions are provided in Table 3 (Khalid et al., 2017).

8.3.1.2.4 Modeling of the DG:

The equation of DG system is discussed in Table A. 1, Sl. No.: 5, Eq. i in SI (Ramesh & Saini, 2020).

The details of DG component is discussed in Table 8.2 (Mandal et al., 2018).

8.3.1.2.5 Modeling of converter system:

The equation of the converter system is discussed in Table A. 1, Sl. No.: 6, Eq. i in SI (Emad et al., 2021). The considered converter system is discussed in Table 8.2. The efficiency is approximately 96% (Das & Al-Abdeli, 2017).

8.3.1.3 Economic modeling:

8.3.1.3.1 Cost of Electricity

The COE is shown in Eq. i, in Table A.2, Sec. 2.ii of SI (Mandal et al., 2018).

8.3.1.3.2 Operational and Maintenance (O&M) cost:

The O&M cost is shown in Eq. i, in Table A.2, Sec. 2.iv of SI.

The penalty cost for the capacity shortage and the carbon emission penalty costs are shown in Eqs. i-ii, Sec. 2.v in Table A.2 of SI.

8.3.1.3.3 Net Present Cost (NPC):

The NPC is shown in Eqs. i-iii, in Table A.2, Sec. 2.i of SI (Nag & Sarkar, 2018).

8.3.2 Objective functions:

For this analysis, an objective function is defined with optimization variables and associated constraints. Cost minimization is the objective function for this problem. The objective function is formulated based on the equations available in literature (Ma et al., 2018). Equation 8.1 represents the objective function.

$$Minimize\ C_{min} = \min(\sum_{i=1}^{I} CI.N_C + \sum_{i=1}^{I}\sum_{j=1}^{J} C_{O\&M}.N_c + \sum_{i=1}^{I}\sum_{j=1}^{J} C_{rep}.N_c + C_{diesel}.N_c) \quad (8.1)$$

In Eq. 8.1, C_{min} is the minimum cost function, CI is the initial expenditure, $C_{O\&M}$ is the O&M rate of the system, C_{rep} is the system's additional price, C_{diesel} is the fuel price. All these costs are in US$/kW. N_c is the capacity of each of the components (kW).

8.3.3 Energy dispatch control strategy:

The dispatch strategies are used to manage the energy balance of the overall energy system. These strategies maintain the proper usage of generator and battery bank at the time of load fluctuation and insufficient renewable resources to obtain the local energy requirement (Ramesh & Saini, 2020). Selection of the suitable dispatch strategy is to achieve the optimal techno-economic solution with minimum CO_2 emission from the hybrid systems. Three different dispatch strategies are available, viz., LF, CC, and CD. The RF is shown in Eq. i, in Table A.2, Sec. 3.i of SI.

In this study, only LF and CC dispatch strategies are considered for the analysis. The previous analysis (Das & Zaman, 2019) showed that both the emission and excess electricity production are much higher for the CD strategy. Hence, it is not considered for this analysis.

8.3.3.1 Load Following (LF) dispatch strategy:

In this strategy, when the available alternative energy is lower than the load demand, DG primarily supplies electricity to the load rather than recharging the batteries (Ramesh & Saini, 2020).

In this strategy, P is the excess power generated by the renewable resources after satisfying the instantaneous load, P_{ren} is the output power from the renewable resources, P_{load} is the load power, SOC is the state of charge of the storage module, P_{DG} is the power supplied by the DG.

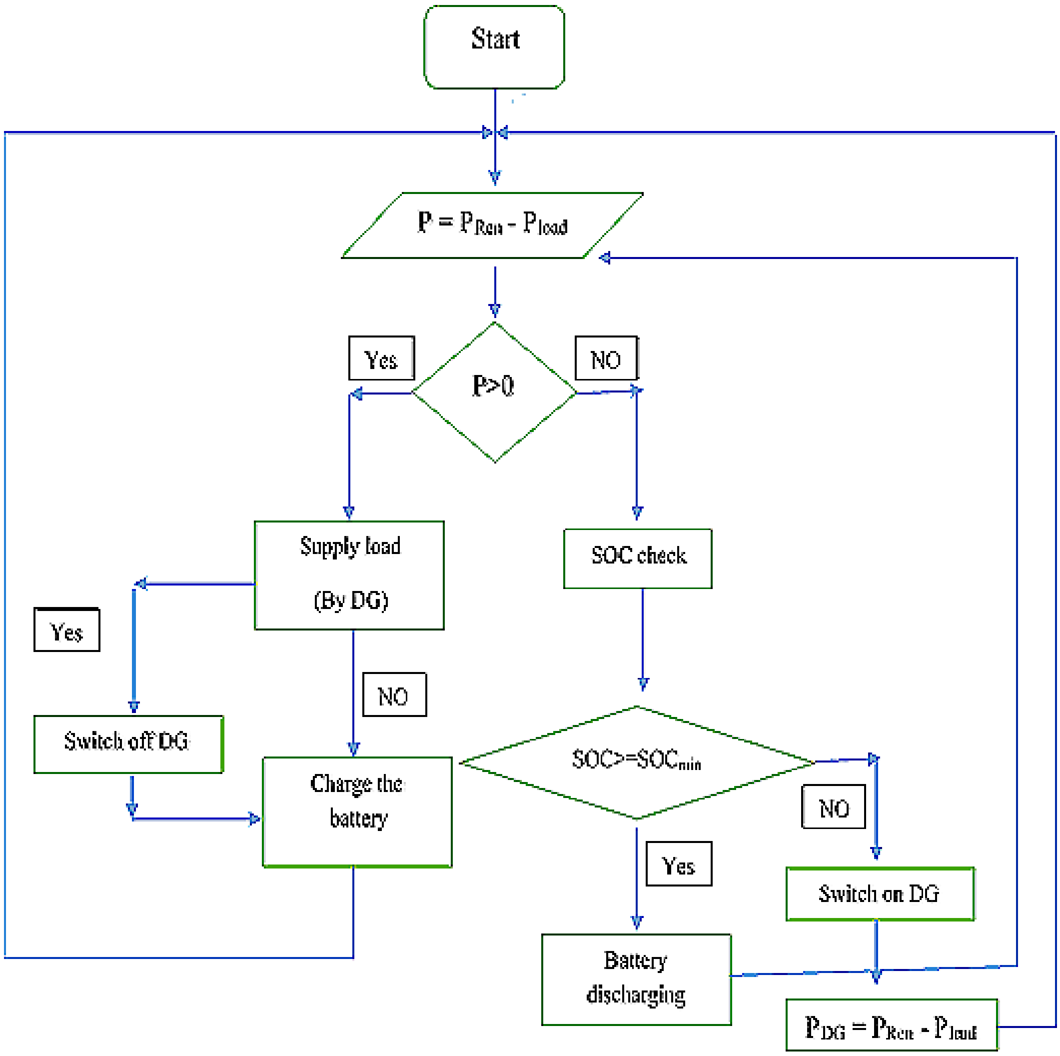


Fig. 8.5: LF dispatch strategy (Das & Zaman, 2019)

According to the logic as shown in Fig. 8.5, the initial stage is the power balance condition (P_{ren} = P_{load}) which is assumed as an ideal state. If the excess electricity occurs i.e., P>0 then the arrangement charges the storage component by using the alternative power and DG is not in operation. But if this alternative resource output becomes less as compared to the load power (P<0) then the storage unit supplies the needed power if the storage system SOC is higher than or equal to the lowest SOC level. But if SOC is less than the minimum SOC level then the DG comes into action and provides the necessary energy. When the available renewable energy is more than the load demand, then the DG system is switched off and the excess renewable electricity is used to recharge the storage unit.

8.3.3.2 Cycle Charging (CC) dispatch strategy:

In this energy dispatch strategy, when the renewable energy deficit occurs, DG starts charging batteries with its full capacity on a priority basis to protect the minimum (Ramesh & Saini, 2020).

In this dispatch analysis, P is the available power after the power generated from renewable resources to meet the load power, P_{ren} is the power output from the alternative resources, P_{load} is the load power, SOC is the state of charge, P_{DG} is the power supplied by the DG.

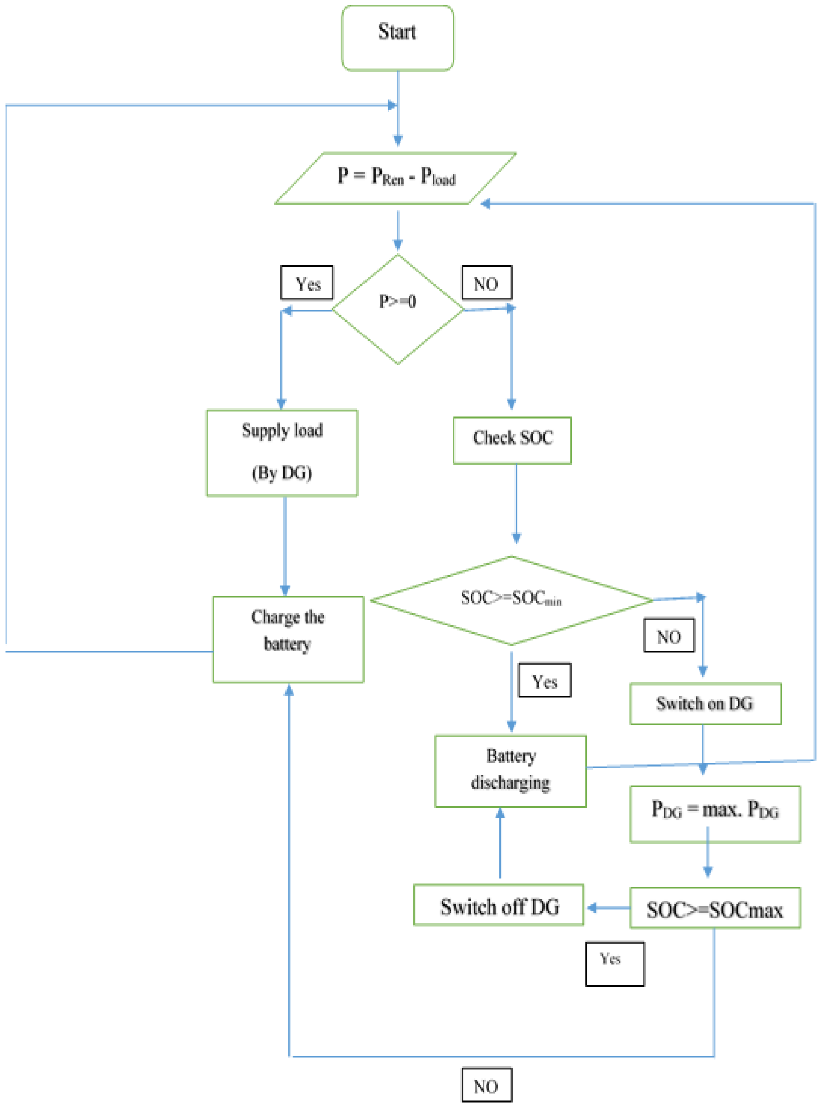


Fig. 8.6: CC dispatch strategy (Das & Zaman, 2019)

According to the strategy shown in Fig. 8.6, if the state of charge becomes less than SOC_{min}, then the DG system starts operating at its maximum power and recharges the batteries until SOC becomes 80%. In CC dispatch strategy, the DG system operates to meet the primary load and also charge the battery.

8.3.4 Sensitivity analysis:

To analyze the system's sustainability sensitivity analyses is essential. The economic parameters such as COE of the hybrid combinations are influenced by the variation of different input parameters such as fuel cost, discount rate, total capital cost and the installation cost of the system (Ramesh & Saini, 2020). Therefore, in sensitivity study these parameters are considered for the analysis.

The reliability test is also performed for HRES feasibility. Assured continuous power supply is explored by the reliability analysis. This analysis gives the idea of possible power failure for the hybrid renewable energy model. A few techniques are available to calculate the energy system's reliability. This reliability analysis is generally done by using the methods named LPSP and UL. The details of this methods are shown in Table A.2, Sec. 3 in SI.

8.4 Results and Discussions:

8.4.1 Techno-economic optimization for combinations:

In the initial stage, four different combinations of energy generators such as PV-Battery, Hydro -Battery, PV-Hydro-Battery, and PV-Hydro-DG-Battery are explored to check if each of these systems can meet the load demand.

In this step, conventional storage modules such as LA batteries are considered. The UL, COE, and NPC are considered as the selection criteria. For the simplicity of the comparison, the values of these criteria are normalized, and the results are shown in Fig. 8.7.

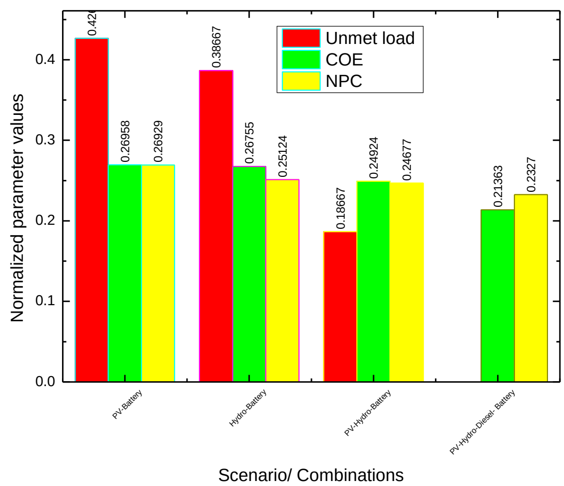


Fig. 8.7: Performance analysis of energy resource combinations

According to this figure, a hybrid combination of PV-Hydro-Battery-DG is techno-economically a better feasible solution as compared to other options. The COE of the four combinations is \$0.530/kWh, \$0.526/kWh, \$0.490/kWh, \$0.420/kWh respectively. The COE and the NPC of the PV-Hydro-DG-Battery combination is approximately 14.285-20.754% and 13-26% lower than other energy combinations respectively. The NPC of this combination is \$4,77,764. Thus, PV-Hydro-DG-Battery is the most feasible techno-economic solution though accommodating some amount of CO_2 emission with a penalty cost. Table 8.3 shows the detailed technical specifications of all the considered scenarios. According to the table, the battery capacity is a maximum with 312 kWh for the selected hybrid system followed by Hydro (118 kW), PV (67 kW), and DG (38 kW).

Table 8.3: Summary of system sizing from HOMER® for different energy resource combinations

Energy combinations	**Individual Capacity of the components**				
	PV (kW)	Hydro (kW)	Battery (kWh)	Converter (kW)`	Generator (kW)
PV-Battery	64	-	114	1.970	0
Hydro-Battery	-	54	212	1.910	0
PV- Hydro-Battery	58	78	235	2.740	0
PV- Hydro-Diesel- Battery	67	118	312	3.560	38

In the next step, analysis is done for comparing the different dispatch strategies and storage modules which are necessary for optimum sizing of the various components of HRES.

8.4.2 Effects of LF and CC dispatch strategy:

Techno-economic performance and CO_2 emission are subsequently studied for five different storage modules (LA, Li-ion, VR, and ZB batteries and PHES) under two distinct dispatch strategies (LF and CC) for the feasible energy option to meet the load demand (i.e., PV-Hydro-DG-battery). Table 8.4 shows the overall energy share and CO_2 emission for different storage modules under two dispatch strategies.

Table 8.4: Hybrid system characteristics with different storage devices

Selected characteristics	**PV- Hydro-DG-LA Battery**		**PV- Hydro-DG-Li-ion Battery**		**PV- Hydro-DG-VR Battery**		**PV- Hydro-DG-ZB Battery**		**PV- Hydro-DG-PHES**	
	LF	CC	LF	CC	LF	CC	LF	CC	LF	CC
PV energy (kWh/year)	29,825	28,344	59,520	54,261	31,514	31,154	11,514	10,514	39,514	31,514
Genset energy (kWh/year)	53,237	58,962	49,520	53,977	54,836	59,784	28,018	39,822	63,485	83,820
Fuel consumption (l/h)	4,865	5,067	4,623	4,855	7,457	8,265	1,085	2,270	9,276	1,1672
Hydro energy (kWh/year)	1,19,520	1,13,496	97,806	79,520	89,520	85,520	79,520	78,520	75,520	74,520
Energy from Storage devices (kWh)	312	359	297.550	309	250	285	220	260	254	291
CO_2 emission (kg/year)	16,823	18,632	15,648.300	17,056	18,276	18,891.700	8,854	12,584	20,061.300	26,487.100

The table shows that under the LF dispatch strategy the solar module produces 1.155% to 25.386% more energy as compared to the CC strategy. Similarly, the hydro energy is 1.273% to 22.995% more under LF dispatch strategy with respect to the CC strategy. However, under CC the energy from the generator is 9.000% to 42.130% higher than the LF dispatch strategy. It is observed that the LF strategy increases the renewable fraction and as a result decreases CO_2 emission. Hence, the CO_2 emission becomes 3.259-29.641% lesser in the LF dispatch strategy. The detailed results of techno-economic performance analysis are shown in Table 8.5.

According to Table 8.5, the COE is comparatively lesser for LF than that of CC. The COE is approximately 0.476-34.113% lower in LF dispatch strategy for LA, Li-ion, VR and ZB batteries. Table 8.5 also shows that the NPC is slightly higher for the CC dispatch strategy. For a hybrid system with LA battery, Li- ion battery, VR battery, and ZB battery the NPC is 4.547%, 8.828%, 13.542%, and 12.169% higher in CC strategy respectively. However, in hybrid systems with PHES storage modules the COE and NPC both are high under LF dispatch strategy as compared to the CC dispatch strategy. The COE is 16.153% and NPC is 2.778% higher for this combination under LF strategy. Though the COE and NPC are high for PHES under LF strategy, Table 8.5 shows that both replacement and O&M costs for the considered hybrid system are higher (20.865% and 19.196% respectively) under CC strategy. A similar result is seen for the capital cost and fuel cost analysis. The capital cost analysis shows that under the LF strategy hybrid system's capital cost is 4.223-16.711% lower as compared to that of CC strategy. The fuel cost result is also similar. It is 0.582-43.911% more under CC strategy than the LF dispatch strategy. According to the analysis, it is visible that for five different modules the RF value is 4.639- 17.562% higher under the LF strategy than that under CC dispatch strategy. Along with the economic analysis, the technical factors for five different storage devices under both of these dispatch strategies are analysed. In this study, two technical aspects are considered. These are the electricity generation and excess electricity produced from the energy system. The technical analysis results are also discussed in Table 8.5. Electricity generation under two dispatch strategies is approximately similar. Whereas the excess electricity is 1.062-10.363% more under the CC strategy.

Table 8.5: Techno-economic analysis results:

	PV- Hydro-DG-LA Battery		PV- Hydro-DG-Li-ion Battery		PV- Hydro-DG-VR Battery		PV- Hydro-DG-ZB Battery		PV-Hydro-DG-PHES	
	LF	CC	LF	CC	LF	CC	LF	CC	LF	CC
COE ($/kWh)	0.420	0.422	0.386	0.396	0.417	0.421	0.197	0.299	0.453	0.390
NPC ($)	4,77,764	4,99,491	5,11,296	5,56,434	5,07,625	5,76,369	3,62,384	4,06,485	5,34,074	5,19,235
Replacement cost ($/kW)	10,019	10,270	8,301	8,545	9,866	10,121	3,959	4,191	2,914	3,522
O&M cost ($/kW/year)	8,401	8,593	6,637	7,307	8,298	9,847	4,461	4,831	5,298	6,315
Capital cost ($)	7,514	7,948	6,190	7,432	6,547	6,921	6,237	6,512	6,475	6,967
Fuel cost ($)	34,864	35,067	24,622	24,854	40,361	42,864	14,085	20,270	39,253	40,276
RF (%)	79.400	75.410	76.200	70.010	67.660	64.660	89.170	84.110	65.600	55.800
Electricity generation (kWh/year)	1,88,798	1,90,285	1,90,214	1,91,341	1,87,564	1,88,655	1,85,261	1,93,291	1,89,674	1,90,345
Excess electricity (kWh/year)	44,823	45,299	54,995	59,722	36,622	37,512	19,300	21,300	35,593	36,537

Table 8.6: Operational emissions:

Carbon and other pollutants (kg/year)	PV-Hydro-DG-LA Battery		PV-Hydro-DG-Li-ion Battery		PV-Hydro-DG-VR Battery		PV-Hydro-DG-ZB Battery		PV-Hydro-DG-PHES	
	LF	CC	LF	CC	LF	CC	LF	CC	LF	CC
CO_2 (mass % of total emission)	16,823 (97%)	18,632 (94%)	15,648.300 (95%)	17,056 (94%)	18,276 (94%)	18,891.700 (94%)	8,854 (98%)	12,584 (96%)	20,061.300 (95%)	26,487.100 (96%)
CO	197.250 (1.14%)	493.790 (2.5%)	348.370 (2.12%)	360.140 (1.99%)	390.070 (2.12%)	391.710 (1.95%)	94.560 (1.04%)	226.450 (1.72%)	350.070 (1.65%)	461.710 (1.66%)
SO_2	98.900 (0.57%)	276.320 (1.4%)	187.640 (1.14%)	246.230 (1.36%)	354.230 (1.82%)	360.020 (1.8%)	54.620 (0.6%)	146.320 (1.11%)	324.230 (1.53%)	360.020 (1.3%)
NOx	136 (0.78%)	337.520 (1.7%)	274 (1.67%)	345.230 (1.91%)	387.230 (1.99%)	390.310 (1.94%)	59.560 (0.66%)	194 (1.47%)	357.230 (1.7%)	390.310 (1.4%)
UHC	7.260 (0.04%)	52.300 (0.26%)	10.230 (.06%)	50.600 (0.28%)	10.3600 (0.05%)	12.360 (0.06%)	6.320 (0.07%)	10.320 (0.08%)	10.360 (0.05%)	12.360 (0.04%)
PM	0.523 (0.003%)	0.780 (0.004%)	0.632 (0.0038%)	0.870 (0.0048%)	0.745 (0.0038%)	0.840 (0.0042%)	0.120 (0.00132%)	0.690 (0.005%)	0.745 (0.003%)	0.840 (0.003%)
Total Pollutants	17,262.900 (100%)	19,792.700 (100%)	16,469.170 (100%)	18,059.070 (100%)	19,418.640 (100%)	20,046.940 (100%)	9,069.200 (100%)	13,161.800 (100%)	21,103.900 (100%)	27,712.340 (100%)

Besides analysing the techno-economic performances, this study also estimates other significant emissions. Estimated emissions are shown in Table 8.6. It is clear from Table 8.6 that the number of other emissions is negligible compared to carbon emission, specifically CO_2. Hence, the environmental impact of this system is subsequently estimated with the CO_2 emission only. As shown in Table 8.6, Carbon dioxide (CO_2) emission for meeting the load demand of 400 households is lesser in LF strategy. It is observed from Table 7, that the amount of CO_2 emission is 3.259-29.641% lower under the LF strategy as compared to that of CC strategy. As a case study for Li-ion batteries, 4,623 l of diesel is consumed to generate 49,520 kWh/year electricity. Hence, the emission factor for the DG power generation is 0.316 kg CO_2/kWh. No emission from other (i.e., renewable) power generating units and batteries during operation is considered. On the basis of the techno-economic analysis and CO_2 emission (as the major environmental pollutant in this study) performance, LF dispatch strategy is better than CC dispatch strategy. After the dispatch strategy selection, this study explores the feasible storage system for the energy model. The detailed discussion of this comparative analysis is done in the next section.

8.4.3 Effects of storage devices on system performance:

At this stage, the effects of different storage modules on the performance of the integrated energy system are analysed under the chosen dispatch strategy (i.e., LF strategy) only. The storage device is a critical module of this integrated hybrid renewable system with DG support and has a great impact on overall energy efficiency, economy and emission. The selection of appropriate storage devices is essential to increase the hybrid system's efficiency by minimizing the economic and environmental impacts. The economic analyses for five different storage devices are shown in Table 8.5. According to this table, the COE is minimum for PV-Hydro-DG with ZB battery (approximately \$0.197/kWh) followed by Li-ion battery (\$0.386/kWh), VR battery (\$0.417/kWh), LA battery (\$0.420/kWh), and PHES (\$0.453/kWh). The NPC value of the hybrid system attached with ZB battery is lower (\$3,62,384) than LA battery (\$4,77,764), VR battery (\$5,07,625), Li-ion battery (\$5,11,296), and PHES (\$5,34,074). Similarly, the cost of O&M is lower when a hybrid system is combined with ZB storage. After the economic assessment of the storage devices the technical analysis is performed, and the result of this analysis is shown in Table 8.7.

Table 8.7: Storage performance on hybrid systems using different dispatch strategies:

Storage unit characteristics	PV-Hydro-DG-LA Battery		PV-Hydro-DG-Li-ion Battery		PV-Hydro-DG-VR Battery		PV-Hydro-DG-ZB Battery		PV-Hydro-DG-PHES	
	LF	CC	LF	CC	LF	CC	LF	CC	LF	CC
Number of Battery (Strings)	64	51	69	58	48	48	90	61	-	-
Storage depletion (kWh/year)	268.500	204	259	222	0	0	244	245	-	-
Nominal capacity (kWh)	289	304	236	249	240	234	207	204	234	240
Usable nominal capacity (kWh)	244	239	230	245	238	230	207	204	201	199
Losses (kWh/year)	6,903	6,950	3,152	3,141	2,213	3,023	2,096	2,736	2,169	3,154
Annual throughput (kWh)	27,909	24,199	33,259	32,842	22,473	25,163	84,750	97,734	23,541	32,581
Lifetime throughput (kWh)	4,32,488	4,31,121	1,88,883	2,63,857	1,19,453	1,23,260	5,42,750	9,32,025	97,254	1,07,523
Lifetime (year)	11.3	7	15	8	20	20	10	10	25	25

This technical analysis is performed under both the dispatch strategies. Capacity of each storage device is so selected that load demand on the distributed generation system is met with 100% reliability. Selection of storage devices is decided accordingly.

As shown in Table 8.7, the nominal capacity of the ZB battery system is moderate (207 kWh). It also operates at full nominal capacity value. This reduces the initial cost as well as the COE amount for the ZB battery systems. Though the usable nominal capacity of VR battery and Li-ion battery are also closer to nominal capacity, their nominal capacity value is higher than ZB battery which increases the COE of these storage devices. The annual throughput is high for the ZB battery. The similar trend is followed for the lifetime throughput of the storage devices. The table 8 also shows that the loss is maximum in the LA storage module. In the ZB battery device the storage loss is the least. It is 69.636% less than the LA battery device. This increases the efficiency of the ZB battery. Also, this technical analysis showed that lifetime throughput is comparable for these storage devices. The annual throughput value in the ZB battery unit (84,750 kWh for LF) is greater than any other storage unit due to which the lifetime throughput is also high (5,42,750 kWh under LF strategy) in this unit as compared to other storage devices. The lifetime of PHES is maximum, which is 25 years, similar to the project lifetime followed by VR storage module (20 years) and the ZB storage module (10 years). The lifetime of LA batteries is minimum (approximately 11.3 years).

To comprehend the storage device performance, along with techno-economic analysis, the storage systems SOC analysis is required. The SOC analysis of LA battery, Li-ion battery, VR battery, ZB battery, and PHES storage devices are shown in Figs. 8.8 (a-e). Figures 8.8. a-e represents the yearly SOC (in %) for the storage devices. According to these figures, the minimum SOC levels for LA and Li-ion batteries are 60% and 25% respectively. Whereas, for the other three storage devices, the minimum SOC level is 0%. Due to the full utilization of charges the efficiency of these three storage devices increases. Though VR batteries and PHES are able to utilize full charges, they require more charging time. This reduces the energy efficiency of the system. Also, due to the very fast charging time, it demands more power from the resources. Thus, the ZB battery device has full discharge capacity and the charging rate is moderately high as compared to VR battery and PHES. Because of full discharge capacity the efficiency of the ZB battery module is higher than other storage modules. Considering the techno-economic and environmental performance analysis it is evident that it is preferred for the proposed energy system of the study area than the other storage modules. Thus, the analysis result signifies that a hybrid energy system (PV-Hydro-DG) with ZB battery module under LF strategy is the feasible optimum sustainable energy solution to efficiently meet the electricity demand of the locality at a minimum cost (i.e, COE- \$0.197/kWh, NPC- \$3,62,384). The RF (89.170%) value is high for this combination which reduces the CO_2 emission (8,854 kg/year). The emission is approximately 29.641% lower under LF strategy as compared to the CC strategy.

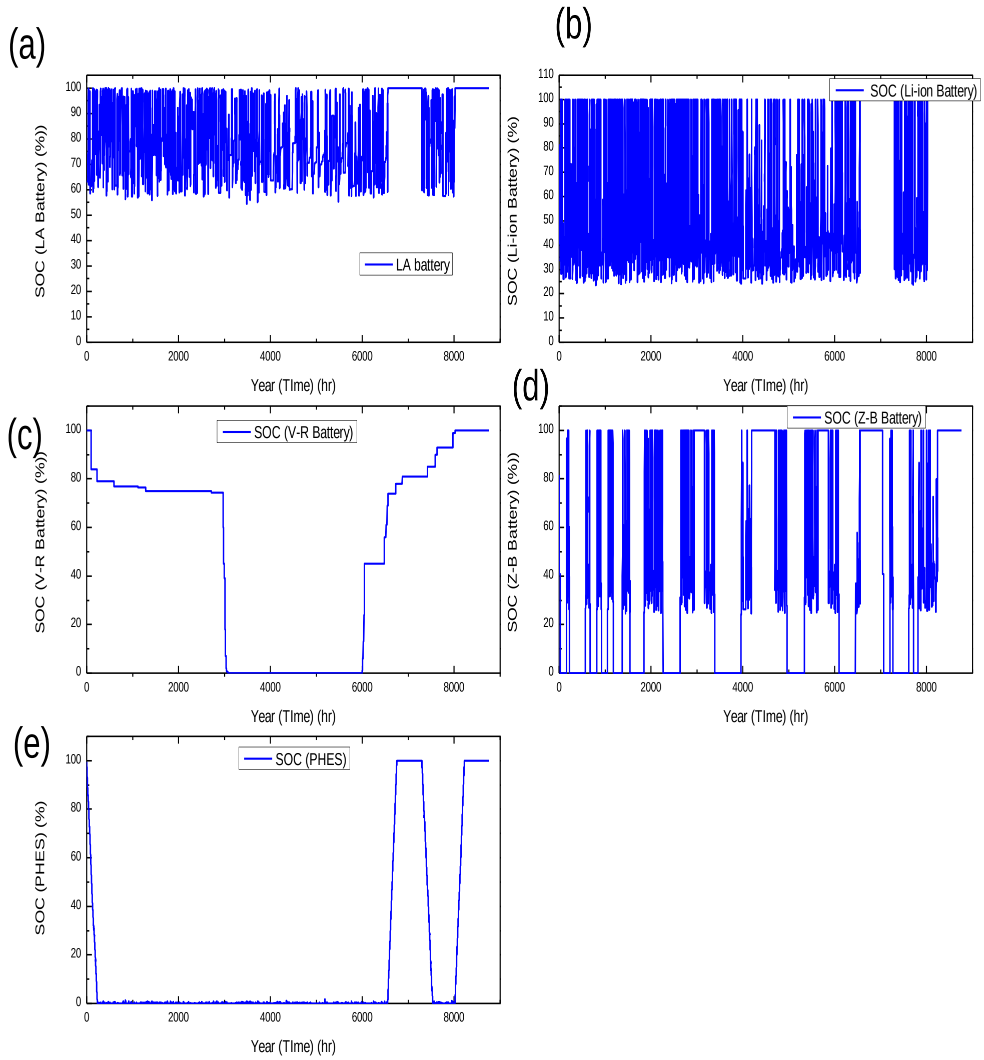


Fig. 8.8: Yearly SOC analysis of different storage devices attached with the hybrid system

The study also shows the varying output power from the final optimum integrated energy system with suitable storage and dispatch strategy for any active week in winter. Figure 8.9 shows the output power variation during the first week of October. According to this figure, solar energy output is less than Hydro energy output. The maximum load demand is met through Hydro energy output. The excess energy is stored in a storage module. If the Hydro energy is unavailable then the solar energy meets the full energy demand. When energy output together from solar and Hydro is unable to meet the load demand during the time of peak demand, supply from the storage module is used to fill the gap between the demand and the supply. The required use of DG is very little and it is only used if the above resources (including storage) are unable to meet specific peak demands. The higher use of renewable resources and storage modules and the restricted use of DG reduce the emission. The optimal system is a feasible solution to meet the local demand as well as techno-economically and environmentally (specifically CO_2 emission) best performing.

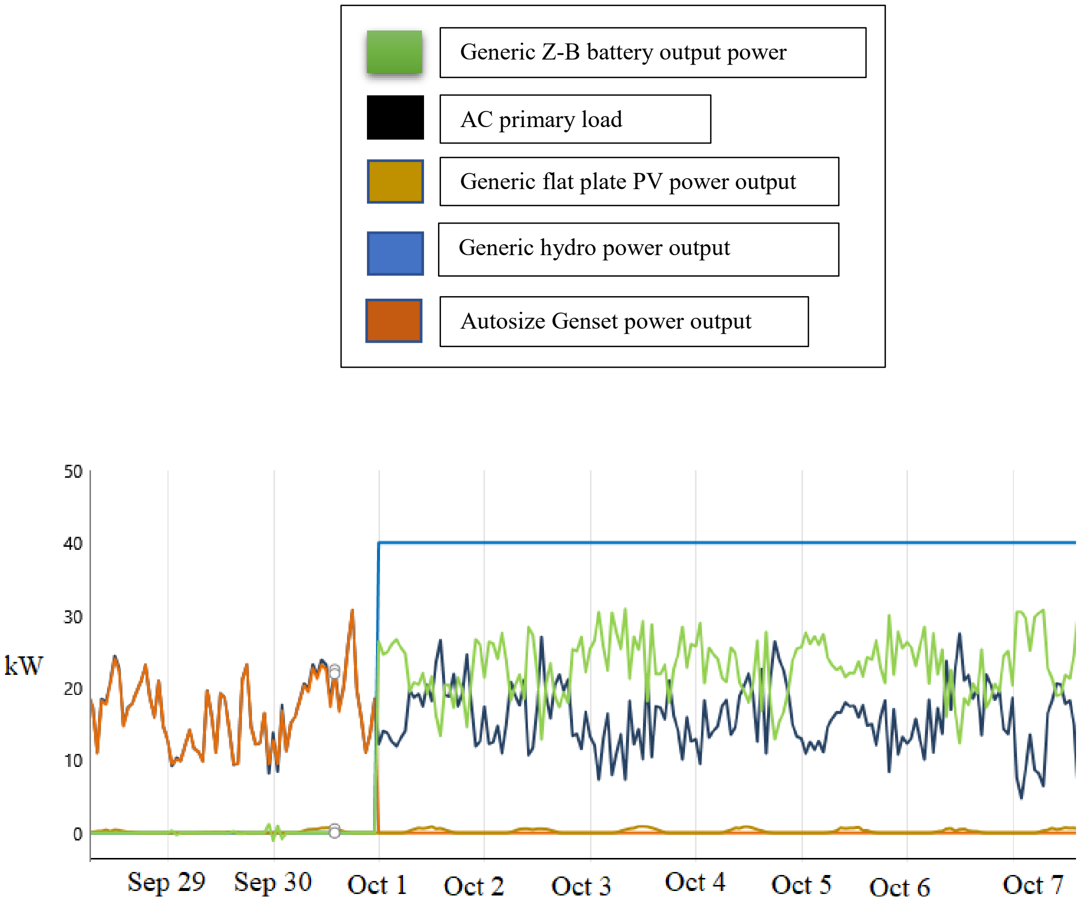


Fig. 8.9: Output power variation of HRES components (PV-Hydro-Z-B-DG) for a week under LF strategy

At the final stage of analysis, this study also assesses the sensitivity and the reliability of the optimal model as discussed in the next section.

8.4.4 Sensitivity and Reliability analysis:

In the sensitivity analysis, the variation of optimum system's COE and NPC with different cost parameters is assessed to check the system's possible future cost vulnerability. Each cost parameter is varied between 40-160%. The analysis result is shown in Fig. 8.10.

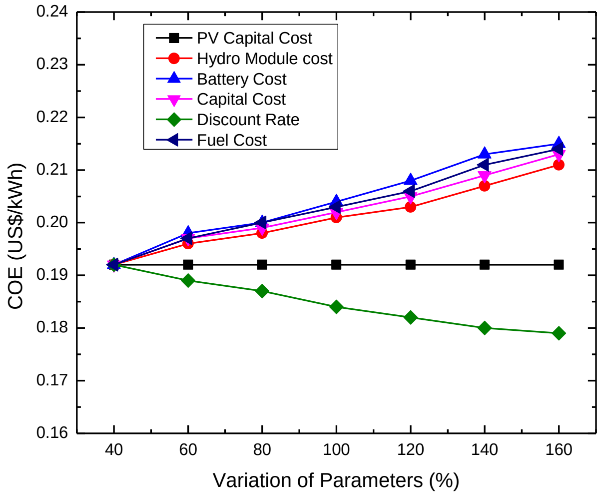


Fig. 8.10: Sensitivity analysis on COE (for the ZB storage device)

The comparison starts from 100%. According to the analysis, the variation of PV cost module on COE is negligible. The variation in cost of the hydro module has more impact on energy system's COE as compared to the PV module cost. With the variation in cost of the hydro module the COE increases significantly (4.688%). The hybrid system's COE simultaneously increases due to the variation of other economic parameters. Due to the variation in fuel cost, capital cost and in the battery cost, the COE increases by 5.729%, 5.208% and 6.250% respectively. However, with the increase of discount rate COE reduces up to 5.729%. This analysis shows that high discount rate reduces the system COE significantly. Therefore, to maintain the economic balance it is required to restrict the discount rate variation. This analysis simultaneously shows that input economic factors like battery cost, fuel cost and system's capital cost may have greater impacts on COE from the optimum integrated hybrid option with storage.

Figure 8.11 represents the sensitivity analysis of the energy system's NPC due to the variation of economic input parameters. The variation is very negligible ranging from 0.006% - 0.016%.

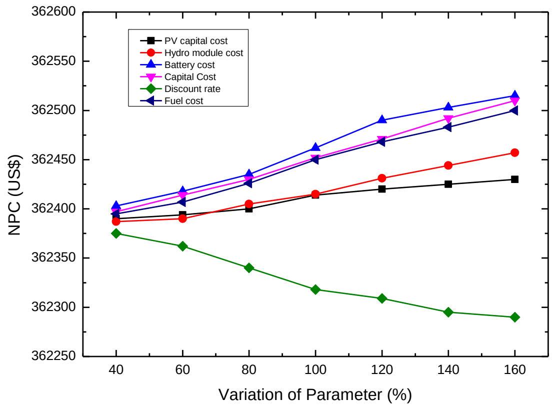


Fig. 8.11: Sensitivity analysis on NPC (for the ZB storage device)

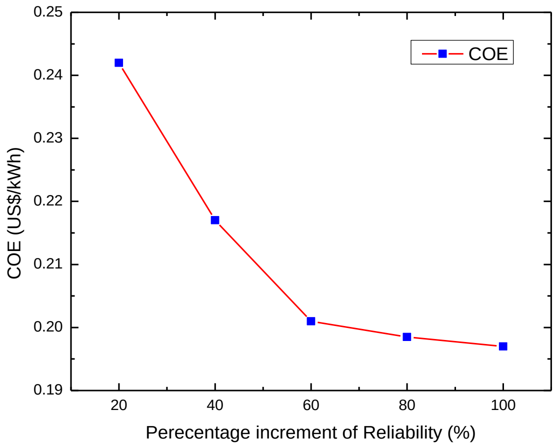


Fig. 8.12: Reliability vs COE analysis

The reliability analysis examines the continuity of the power supply without failure. The analysis result is shown in Fig. 8.12. According to Fig. 8.12, the optimized COE is achieved when the reliability is also 100% as no revenue loss happens during operation without any power failure. According to the figure, for 20%, 40% and 80% reliable conditions the COE is 22.483%, 10.152% and 0.761% higher with respect to the 100% reliable condition. In a renewable energy system, capital cost is much higher than the operational cost. When the reliability is low the operational cost becomes low but the capital cost remains unchanged. Moreover, no revenue can be generated during the hours of power failure. For this reason, the COE becomes higher with the increase in hours of failure of power supply.

Uninterrupted reliable power supply assures better economic and social solutions. Hence, PV-Hydro-DG with ZB storage media emerges as the most reliable hybrid combination of power supply with lesser COE and CO_2 emission.

8.5 Summary of the chapter:

This study compared different storage modules and dispatch strategies for a feasible optimum hybrid energy system to meet the local load demand for a minimum cost including CO_2 emission. The optimum solution for uninterrupted power supply at a minimum cost including penalty due to CO_2 emission is the ZB battery module combined with a hybrid system (PV-Hydro-DG) under the LF dispatch strategy. The corresponding COE, NPC, and RF for this optimal solution are $0.197/kWh, $3,62,384, and 89.170% respectively. The COE and NPC are 0.476-34.113% and 4.547-13.542% lower under the LF dispatch strategy than CC strategy respectively (except in PHES based hybrid energy system. COE and NPC of this system are 16.153% and 2.778% higher for LF strategy as compared to the CC strategy). The CO_2 emission is approximately 3.259-29.641% lower under LF strategy. Simultaneously, in LF strategy renewable energy share is 4.639-17.562% higher than CC strategy. Under LF strategy the COE and NPC of the ZB storage is 34.114% and 10.849% less and 29.641% lesser CO_2 emission as compared to CC dispatch strategies. Under LF dispatch strategy the economic constraints such as COE, NPC and the environmental constraints like CO_2 emission of ZB storage modules are significantly lesser than other storage modules. The COE is 48.964%-56.512%, NPC is 24.149%- 32.147% and the CO_2 emission is 43.419%- 55.865% lower for ZB storage modules as compared to the other storage devices. The sensitivity analysis also confirmed no significant vulnerability of the COE of the optimum solution with even 100% price variations of inputs. Reliability analysis confirmed lower COE with assured power supply without any failure.

Chapter-9

Techno-economic and investment risk assesment of different 'green' hydrogen with electro-chemical storage options*

(***Das, S.**, Pradhan, S., De, S.* (2023): Multi criteria decision making for the most suitable combination of energy resources for a decentralized hybrid energy solution with green hydrogen as storage. **Energy Conversion and Management (Elsevier) (Published). DOI:** https://doi.org/10.1016/j.enconman.2023.117028)

9.1 Objective of the work:

A novel option may be to use this produced hydrogen using excess renewable power during off-peak load. Subsequently this green hydrogen may be used to supply power demand gap during peak load by fuel cells (FC). This paper explores a comparative economic performance assessment as well as the risk of investment of existing and new options to bridge the gap between demand and supply during operation. This is done through comparative evaluation of techno-economic parameters of these options. The uncertainties in ROI are also determined by MCS. As the parameters do not converge to the same option, a MCDM approach is applied to decide the best acceptable option using these criteria with decided weights. Robustness of the determined solution is also checked by a follow up sensitivity analysis.

9.2 Study area selection:

The proposed generic methodology is demonstrated with Indian data. To perform the analysis Gobardhanpur, a remote village of Sunderban, West Bengal is considered. The latitude and longitude are 22.70ºN and 88.69ºE respectively (Map, 2020). The district is socio-economically poor without any grid power. The centralized grid system to this area is techno-economically not feasible due to its difficult terrain condition (Alzajeera, 2021). Figure 9.1.a-c represents the location in the Indian map and the socio-economic condition of the area (G. of India, 2011).

(a) (b)

(c)

Fig. 9.1. a. Location in Indian map, b. Demographic location, c. socio-economic condition (G. of India, 2011)

9.3 Materials and Methodology:

To select an appropriate decentralized energy combination with suitable storage device through techno-economic analysis followed by financial risk assessment is performed. In this study, the generated EE is converted to hydrogen during off-peak load. Subsequently this green hydrogen may convert to electricity by FC during peak load. The study assesses the practical feasibility of this option with respect to the commonly used electrochemical storages such as LA and Li-ion battery based on the decided techno-economic and financial risk factors. The schematic diagram of the system is shown in Fig. 9.2.

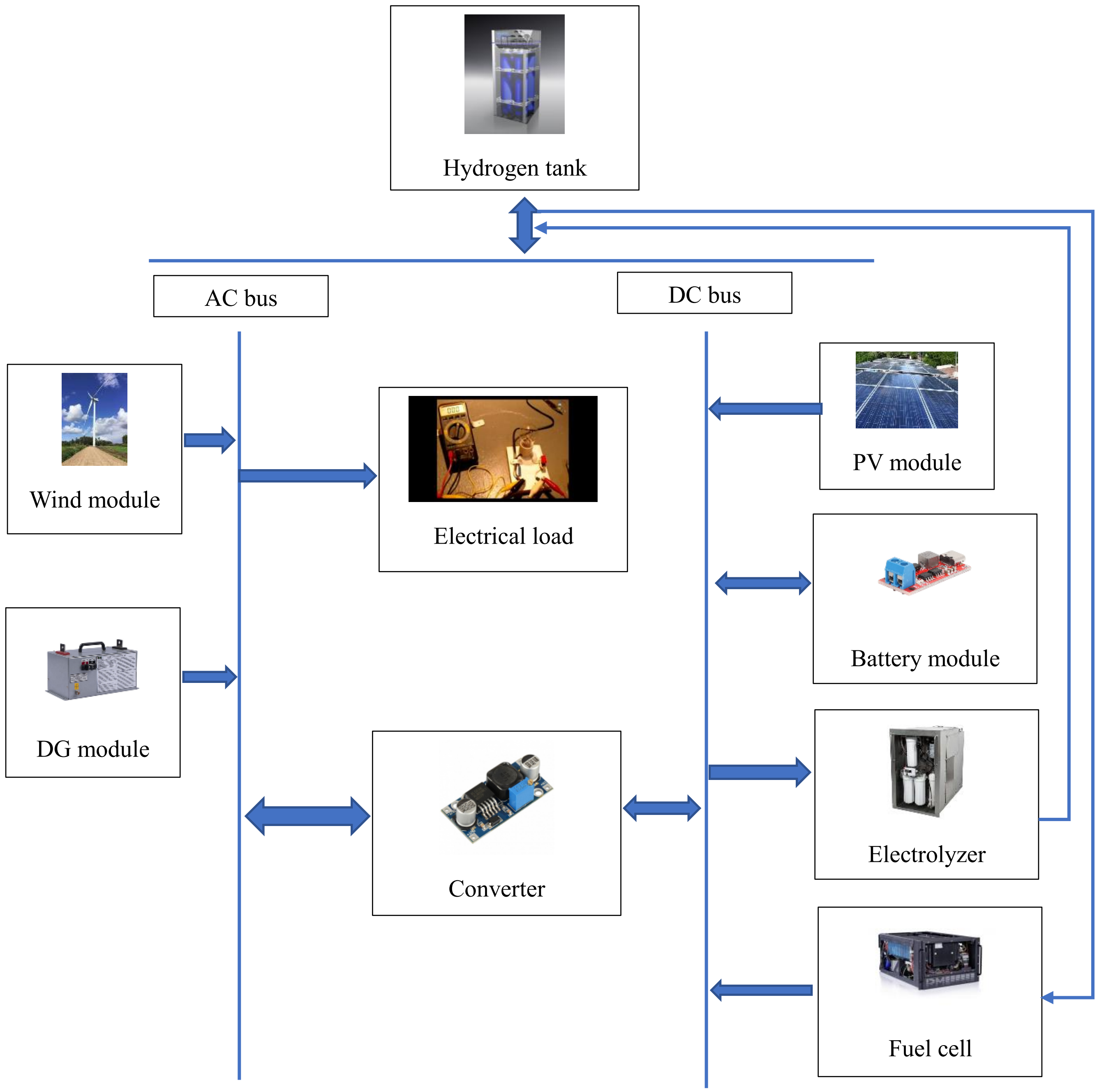


Fig. 9.2: Schematic diagram of the system

9.3.1 System modelling:

According to Fig. 9.2 the considered important modules are solar PV module, wind module, DG module, conventional electro-chemical battery systems (LA and Li-ion), electrolyzer, fuel cell (FC), converter and hydrogen tank. The details of these modules are discussed later.

9.3.1.1 PV system modelling:

The output power of the PV module is discussed in equations shown in Table A. 1, Sl. No.: 1, Eqs. i-iii (Babatunde et al., 2022; Emad et al., 2021; Mandal et al., 2018) in Supplementary Index (SI).

A flat-plate PV is considered in this study (Khan et al., 2021). The details of the module are shown in Tables 9.1 and 9.2.

The monthly average solar radiation data for the considered study area is obtained from NASA weather report (NASA, 2022b). It is used as input for the optimization process. The solar radiation and clearness index is shown in Fig. 9.3. The average solar radiation and the temperature are 4.63 kWh/m^2/day and 27°C.

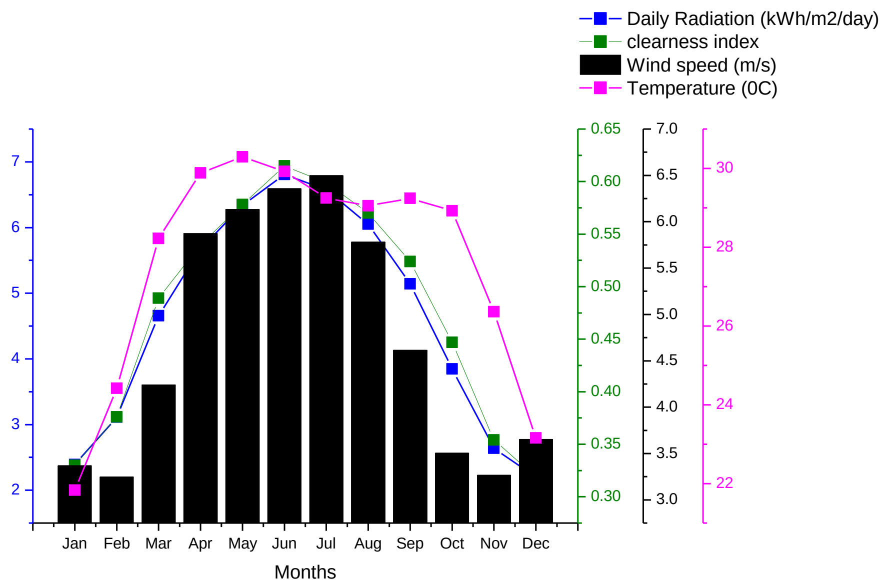


Fig. 9.3: Resource data (NASA, 2022)

9.3.1.2 Wind turbine modelling:

The output power of the wind module is discussed in equations shown in Table A. 1, Sl. No.: 2, Eqs. i-iii (Emad et al., 2021) in SI.

The wind speed is obtained from NASA weather report and the data is plotted in Fig. 9.3 (NASA, 2022b). According to the data obtained the wind speed varies from 3.2m/s to 6.5m/s. The wind speed is moderate with an average of 4.71m/s.

Considering the wind speed of the area a 3kW wind turbine is used for this study. The detailed techno-economic data is shown in Tables 9.1 and 9.2 (Khan et al., 2022).

9.3.1.3 Storage system modelling:

The equations of storage systems are discussed in Table A. 1, Sl. No.: 4, Eqs. i-v in SI (Baneshi & Hadianfard, 2016). As an electro-chemical storage module this study considered a 12V, 1kWh LA and Li-ion battery. The detailed techno-economic specifications of the module are discussed in Tables 9.1 and 9.2 (Khan et al., 2021).

9.3.1.4 Converter modelling:

The equation of converter system is discussed in Table A. 1, Sl. No.: 6, Eq. i in SI (Emad et al., 2021).

A 1kW parallel connected boost converter is considered. The detailed techno-economic specifications are shown in Tables 9.1 and 9.2 (Khan et al., 2021).

9.3.1.5 DG modelling:

The equation of the DG system is discussed in Table A. 1, Sl. No.: 5, Eq. i in SI (Ramesh & Saini, 2020).

A diesel generator is used to increase the reliability of the power supply. The lowest capacity diesel generator is used. The details of the module are shown in Tables 9.1 and 9.2 (Khan et al., 2021).

9.3.1.6 Electrolyzer modelling:

The equation of DG system is discussed in Table A. 1, Sl. No.: 7, Eq. i in SI (Mehrjerdi et al., 2022).

A generic Electrolyzer is used in this study, the specifications are given in Tables 9.1 (Mehrjerdi et al., 2022) and 9.2 (Praveenkumar et al., 2022).

9.3.1.7 Hydrogen tank modelling:

The hydrogen produced by the Electrolyzer is stored in a hydrogen tank. This stored hydrogen is used to produce electricity whenever there will be a shortage of electrical power. The amount of hydrogen stored inside the tank is calculated by Eq. I in Table A.1, Sec. 8 (SI) (Mehrjerdi et al., 2022)

A generic hydrogen tank is considered in this study and the techno-economic details of the tank is provided in Tables 9.1 and 9.2 (Praveenkumar et al., 2022).

9.3.1.8 Fuel cell modelling:

A fuel cell is an electro-chemical device that converts the chemical energy directly into electrical energy. The electricity generation from fuel cells is calculated by using Eq. I, Table A.1, Sec. 9 (SI) (Praveenkumar et al., 2022).

The proton exchange membrane (PEM) fuel cell is used in this study. The techno-economic details of the fuel cell are described in Tables 9.1 and 9.2 (Praveenkumar et al., 2022).

Table 9.1: Economic specifications (Khan et al., 2021; Mehrjerdi et al., 2022; Praveen Kumar et al., 2022)

Module	Capital cost ($/kW)	Replacement cost ($/kW)	O&M cost ($/kW/year)
PV module	950	800	10
Wind module	1980	980	10
LA battery	250	200	2
Li-ion battery	300	300	10
Electrolyzer	100	100	8
Hydrogen tank	1500	500	150
Diesel generator	250	160	1.34
Fuel cell	450	400	0.15 per hour

Table 9.2: Technical specifications (Khan et al., 2021; Mehrjerdi et al., 2022; Praveen Kumar et al., 2022)

Components	Parameters	Specifications
PV Module	Derating factor	90 %
	Panel type	Flat type
	Lifetime	20 years
	Capacity	10 kW
Wind Turbine	Rated capacity	3 kW
	Lifetime	20 years
	Hub Height	17 m
Diesel Generator	Lifetime	15000 hours
	Minimum load ratio	25 %
	Fuel Price	1.2 $/L
	Fuel Curve intercept	4.67 L/hr
	Fuel Curve slope	0.236 L/hr/kW
	Carbon content	88 %
Converter	Lifetime	15 years
	Inverter efficiency	95 %
	Rectifier efficiency	95 %
Electrolyzer	Lifetime	15 years
	efficiency	85 %
	Lifetime	15 years
Li-ion Battery	Roundtrip Efficiency	90 %
	Minimum Soc	20 %
	Initial Soc	100 %
	Nominal Cell Voltage	6V
	Nominal Cell Capacity	1 kWh
	Maximum Charge current	167 A

	Maximum Discharge current	500 A
	Lifetime	10 years
Lead-acid Battery	Roundtrip Efficiency	80 %
	Minimum Soc	40 %
	Initial Soc	100 %
	Nominal Cell Voltage	12 V
	Nominal Cell Capacity	1 kWh
	Maximum Charge current	16.7 A
	Maximum Discharge current	24.3 A
Hydrogen tank	Initial Tank Level	10 %
	Lifetime	25 years
Fuel cell	CHP heat recovery ratio	60%
	Lifetime	50000 hours

9.3.2 Methodology:

The detailed methodology of this study is shown in Fig. 9.4. According to the integrated methodology, the study is focused on finding techno-economically suitable energy combinations with less financial risk. In this study the generated EE is proposed to convert into hydrogen as an alternative storage option. This study compared this hydrogen storage option with the electro-chemical storage modules with respect to techno-economic factors and the risk in ROI. The objective of this analysis is to examine the reliability of the hydrogen storage system as compared to the electro-chemical storage modules and to provide an alternative efficient storage module for the distributed energy supply. The HOMER® is used to perform the techno-economic assessment. To study the economic risk the MCS method is considered in this study. Finally, the MCDM approach is adopted to decide the optimal solution to meet the load demand at an affordable cost with minimum risk in ROI and also with a high RF. The TOPSIS-MCDM is used in this analysis. The sensitivity analysis is performed through VIekriterijumsko KOmpromisno Rangiranje (VIKOR)-MCDM method. The economic factors are COE, NPC and O&M cost, RF, and the risk in ROI (i.e., standard deviation of COE) are the considered factors in this study.

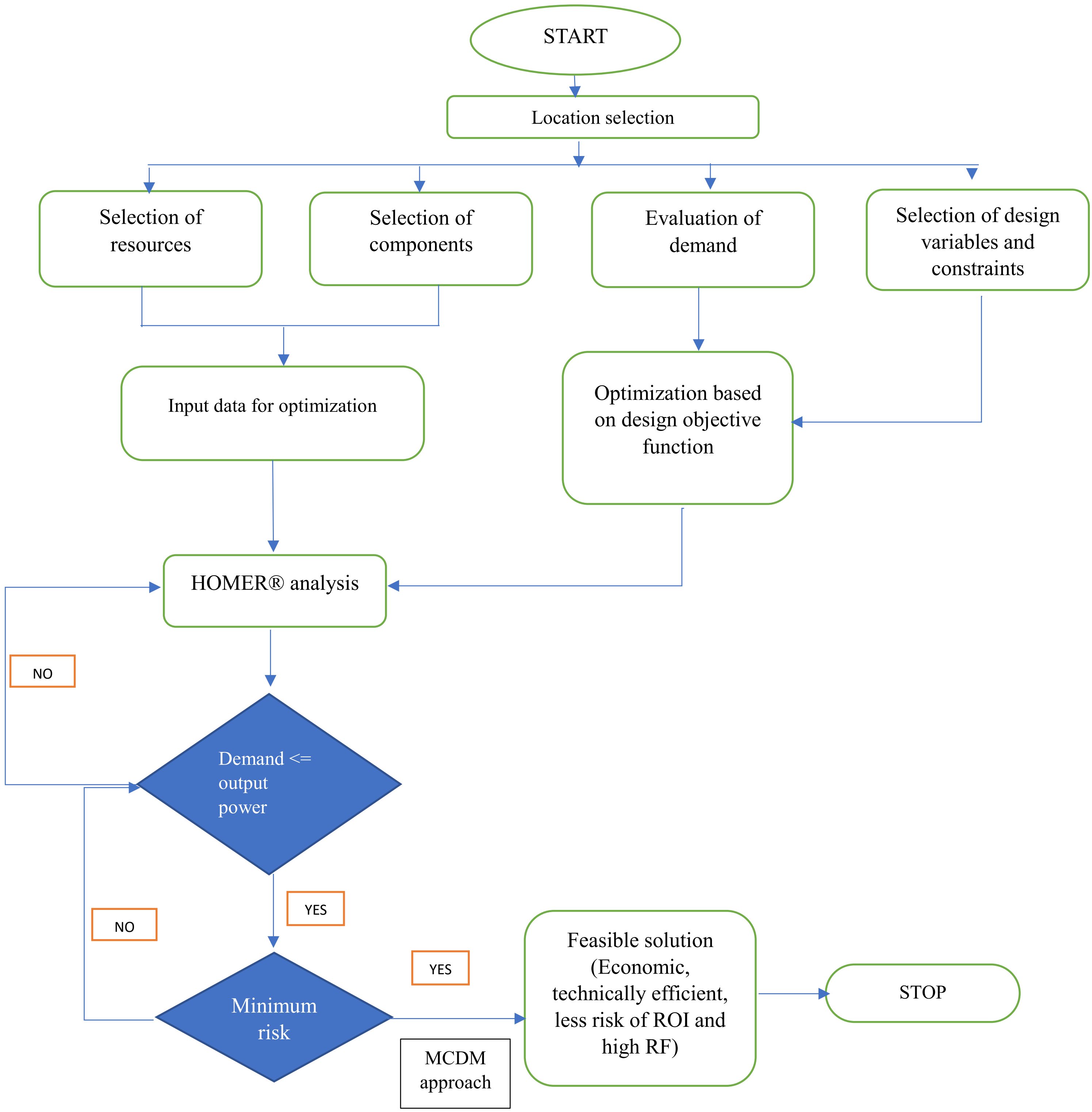


Fig. 9.4: Flowchart of the detailed methodology

9.3.2.1 HOMER® methodology:

The detailed working principle of HOMER® is shown in discussed in Chapter 5, in "Sec. 5.3.3.1: HOMER® methodology"(Ramesh & Saini, 2020).

9.3.2.2 Monte Carlo Simulation:

Monte Carlo simulation (MCS) is an extensively used probability distribution approach to evaluate the risk associated with a forecasted economy. The details of this methodology are discussed in Chapter 7, in "Sec. 7.2.3.2: Monte Carlo Simulation for risk assessment". The input details are discussed in Table 9.3 (Lee et al., 2017).

Table 9.3: Input parameters distribution function (Lee et al., 2017)

	Min	**Max**	**Mean**	**Standard deviation**	**Simulation**
PV					
CAPEX (PV)	641.25	1220.75	931		Exponential
OPEX (PV)	6.75	12.85	9.8		Exponential
Wind					
CAPEX (Wind)	1257.3	2643.3	1950.3		Exponential
OPEX (Wind)	4	20	12		Exponential
DG					
CAPEX (DG)	167.5	332.5	250	82.5	Log-normal
OPEX (DG)	2.2	6.1	4.15	1.95	Normal
Battery					
CAPEX (Battery)	107.1	428.4	267.75	160.65	Exponential
OPEX (Battery)	6	30	18	12	Triangular
Fuel cost ($/Litre)	0.4	2	1.2	0.8	Normal
Discount rate (%)	4	16	10	6	Normal
Solar radiation (kWh/m^2/day)	6	7	6.5	0.5	Normal
Wind speed	5	8	6.5	1.5	Weibull
Battery (LA)					
CAPEX	89.25	357	223.125	133.875	Exponential
OPEX	1.5	6	3.75	2.25	Triangular
hydrogen tank					
CAPEX	535.5	2142	1338.75	803.25	Exponential
OPEX	112.5	450	281.25	168.75	Triangular
Electrolyzer					
CAPEX	75	120	97.5	22.5	Exponential
OPEX	6	24	15	9	Triangular
Fuel Cell					
CAPEX	350	550	450	100	Exponential
OPEX	0.2	01	0.15	0.05	Triangular

9.3.2.3 Multi Criteria Decision Making:

An MCDM approach is used to find the finally decided optimum solution based on technical, economic and renewable fraction data. The TOPSIS is used in this study for the analysis. The VIKOR is finally used to validate the result obtained through the TOPSIS.

9.3.2.3.1 TOPSIS methodology:

The details of the TOPSIS-MCDM method are discussed in Chapter 5, in "Sec. 5.3.3.2.1: TOPSIS-MCDM algorithm".

9.3.2.3.2 VIKOR methodology:

VIKOR algorithm is an MCDM method to solve different decision-based problems with conflicting criteria. This method ranks and selects from a set of alternatives which helps to reach a final decision (Opricovic & Tzeng, 2007). The steps of VIKOR are as follows (Kannan et al., 2021).

Step 1- Determine a pairwise matrix for each alternative.

Step 2 – the average decision matrix is calculated by using Eq. 9.1

$$v_{ij} = \frac{1}{k}\sum_{p=1}^{k} x_{ij}^{p} \tag{9.1}$$

Where i= 1,2,…m and j=1,2…n

Step 3 – The best value (v_j^+) and the worst value (v_j^-) is calculated for all the criteria. The best value represents the positive ideal solution and the worst value represents the negative ideal solution for the criteria j.

Step 4 – The distance from the positive ideal solution and the distance from the negative ideal solution is calculated. The distance of alternative i from the positive ideal solution is S_i and similarly the distance of alternative i from the negative ideal solution is R_i.

Step 5 – Value of Q_i is calculated using the Eq. 9.2

$$Q_i = w\left[\frac{S_i - S^+}{S^- - S^+}\right] + (1-w)\left[\frac{R_i - R^+}{R^- - R^+}\right] \tag{9.2}$$

Where S^- is the $\max_i S_i$, S^+ is the $\min_i S_i$, R^- is the $\max_i R_i$, R^+ is the $\min_i R_i$ and w is the weight of the maximum set utility.

Step 6 – Based on Q_i values the alternatives are ranked. The minimum value of Q_i is obtained such that it satisfies two conditions simultaneously. The two conditions are -

Condition A (Acceptance attribute): Alternative a^1 is selected on the basis of Eq. 9.3

$$Q(a^2) - Q(a^1) \geq \frac{1}{m-1} \tag{9.3}$$

Where a^2 is the alternative with second rank and m is the number of iterations.

Step 7 – The alternative having the minimum Q_i will be ranked first.

9.3.3 Electric load analysis:

The load analysis is shown in Fig. 9.5. Electricity is estimated using a mathematical process (Ramesh & Saini, 2020). During winter, the peak load is 31 kW and the average load is 11.88 kWh/day. During summers, the load demand is the highest with a peak load of 89.53 kW and the average load is 30.24 kWh/day. The average electric load throughout the year is 19.43 kW.

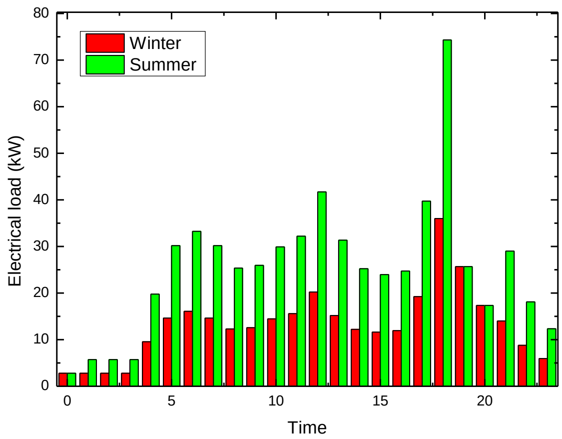


Fig. 9.5: Electrical load analysis

9.3.4 Optimization parameters and objective functions:

The economic, technical and environmental parameters are considered for optimizing a system. In this study the economic parameters consist of attributes- COE, NPC, O&M costs. The UL, EE and fuel consumption (F_C) are considered as technical performance factors and the environmental performance is estimated by the RF parameter.

9.3.4.1 Economic analysis:

To evaluate the economic feasibility of the hybrid energy model a few parameters are considered in this study. The considered parameters are discussed below.

9.3.4.1.1 Cost of electricity (COE):

The COE is shown in Eq. i, in Table A.2, Sec. 2.ii of SI.

9.3.4.1.2 Net Present Cost (NPC):

The NPC is shown in Eqs. i-iii, in Table A.2, Sec. 2.i of SI.

9.3.4.1.3 Operation and maintenance (O&M) cost:

The O&M cost is shown in Eq. i, in Table A.2, Sec. 2.iv of SI.

The penalty cost for the capacity shortage and the carbon emission penalty costs are shown in Eqs. i-ii, Sec. 2.v in Table A.2 of SI.

9.3.4.2 Technical analysis:

The technical efficiency of the energy combinations is determined by estimating the UL during peak hours and EE during lean demand. To optimize the electricity production the component's capacity optimization is essential to produce maximum electricity from the module (Razmjoo et al., 2021).

9.3.4.2.1 Unmet load:

The estimation of UL is shown in Eq. i, Table A.2, Sec. 1.i (SI).

9.3.4.2.2 Excess Electricity:

Excess electricity (EE) is shown in Eq. ii, Table A.2, Sec. 1.ii (SI).

9.3.4.3 Emission analysis:

It is another parameter used for the optimization of the system. RF is considered as the emission performance analysis parameter and it is discussed below.

9.3.4.3.1 Renewable Fraction:

The calculation of RF is shown in Eq. i, Table A.2, Sec. 3.i (SI).

9.3.4.4 Objective function:

Depending on the variables and constraints to perform a techno-economic analysis the objective function is developed. The objective function of this study is shown in Eq. 9.4.

$$F_{obj} = \{\min(COE, NPC, O\&M, UL, FC), \max(RF)\} \tag{9.4}$$

The optimization aims to minimize the economic parameters like COE, NPC and O&M; and technical factors like UL, F_C. Simultaneously maximizing the RF to reduce the emission is also the optimization objective considered in this study.

9.4 Results and Discussion:

9.4.1 Renewable-based system's techno-economic optimization:

At the first step, the techno-economic analysis of only renewable energy combinations is performed. Only the DG energy module is considered in this analysis as a reference system as it is now the only existing one. The COE and UL are considered as the economic and technical performance factors respectively. The analysis result is shown in Figs. 9.6.

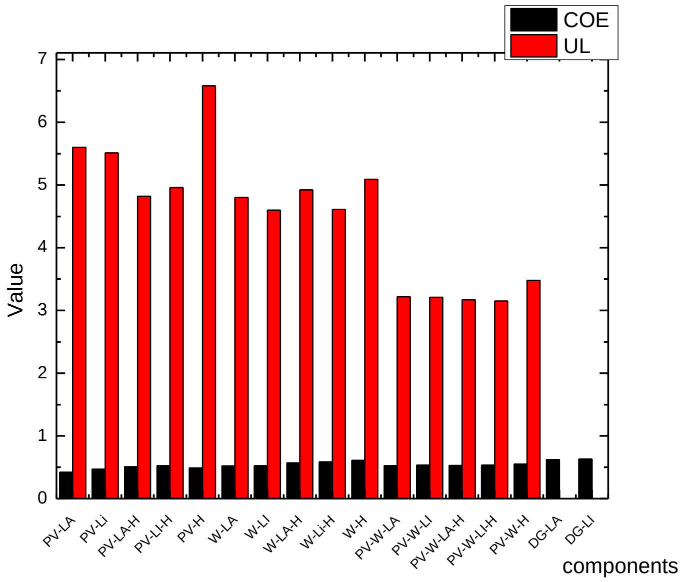


Fig. 9.6: COE of the energy combinations

Figure 9.6 shows that the COE of the combinations are in between \$0.42-0.63/kWh. The maximum COE is obtained for the DG based modules (DG-Li-ion- \$0.631/kWh) and the lowest COE is found for the combination of PV-LA- \$0.42/kWh. The UL is also there in that combination. The maximum and minimum UL is available in PV-LA combination (5.6%) and PV-W-Li-ion-hydrogen (H) combination (3.15%) respectively. The DG energy system meets the total load demand but the emission of this system is high as compared to other modules. The capacity of the decided combinations is optimum. Supplying the rest of the required electricity by increasing the capacity is not feasible because the COE of the energy combinations will exceed the COE of the reference case, i.e., the existing practice. Hence, to meet the UL, the DG is integrated with those combinations and again the techno-economic optimization of those combinations is performed.

9.4.2 Techno-economic optimization analysis:

The techno-economic optimization result of the combinations is shown in Table 9.4.

Table 9.4: Techno-economic analysis results

Energy combinations	COE ($/kWh)	NPC ($)	RF (%)	CO_2 emission (Kg/year)	Fuel consumption (F_C) (L/year)	Simple payback (year)	Electricity production (kWh/year)
PV-wind-gen-hydrogen storage-Li-ion	0.158	4,24,566	96.8	6,567	2,509	4.06	1,71,487
PV-gen-Li-ion	0.159	4,24,568	95.6	6,627	2,819	4.12	1,70,552
PV-wind-gen-Li-ion	0.159	4,24,568	96.5	5,964	2,628	5.01	1,70,652
PV-gen-Li-ion-hydrogen storage	0.168	4,50,419	96.3	5,902	2,720	5.1	1,70,102
PV-wind-gen-LA	0.205	5,51,952	94.3	7,995	3,054	4.6	1,70,852
PV-wind-gen-LA-hydrogen storage	0.206	5,52,994	94.4	7,908	2,991	4.5	1,70,541
PV-Gen-LA	0.237	6,38,112	93	8,206	3,206	6	1,70,701
PV-Gen-LA-hydrogen storage	0.238	6,39,154	92.9	8,216	3,521	5.9	1,70,602
Wind-gen-Li-ion	0.316	8,49,935	80.5	30.659	5, 712	6.12	1,69,981
Wind-gen-Li-ion-hydrogen storage	0.317	8,50,977	80.5	30,659	5,712	6	1,69,981
Wind-gen-LA	0.35	9,55,341	82.9	26,218	4,016	6.2	1,70,552
Wind-gen-LA-hydrogen storage	0.354	9,51,373	82.9	26,218	4,016	6.18	1,70,491
PV-wind-gen-hydrogen storage	0.661	1.77M	84.4	24,216	3,816	5.8	1,70,500

The analysis shows the techno-economic and renewable fraction results of those combinations. Total 13 energy combinations are capable of meeting the required load demand. The COE, NPC, and the simple payback are the economic performance factors. The technical performance factors are electricity production and F_C. The RF and CO_2 emission are the environmental performance factors considered in this analysis.

The study shows that the COE of the considered combinations are 16.8-62.79% less as compared to the only renewable based systems. The UL is met by adding the DG set. The table shows that the minimum COE and NPC is obtained for the combinations of the PV-wind-DG-Li-ion-hydrogen storage ($0.158/kWh and $4,24,566 respectively) followed by the PV-DG-Li-ion and PV-wind-DG-Li-ion combinations. The COE and NPC are similar for both these combinations ($0.159/kWh, $4,24,568 respectively). The COE of the PV-wind-DG-Li-ion-hydrogen storage combination is approximately 75% less than that of the reference system, i.e., DG-based module. The technical performance factor (F_C) is also less for this combination. Hence, for this combination the RF is maximum and it is approximately 96.8%. The high RF of the combinations reduces the CO_2 emission of the system. The result shows that this combination is a low-carbon solution as compared to the other energy systems. After techno-economic and low-carbon analysis in the next step the economic risk assessment of the combinations is done.

9.4.3 Economic risk assessment:

The analysis is conducted to find the uncertainty associated with the investment and it is helpful for the investor to decide. The MCS is applied in this study to perform the risk analysis of the economic parameters. The COE of the energy systems are considered as the main economic performance factor. Therefore, the risk assessment is performed for the COE of the combinations. The variation of the input economic values changes the COE of the combinations. The variation is denoted by the standard deviation in this analysis. If the standard deviation of the modules is high it increases the economic uncertainty of the combinations. The MCS analysis of the combinations are shown in Fig. 9.7. Table 9.5 shows the detailed variation and standard deviation of the combinations. Figure 9.8 shows the curve fitting of the economic risk analysis.

Table 9.5: Economic risk assessment:

Statistic	**COE (PV-G-LA)**	**COE (PV-G-LA-H)**	**COE (PV-G-LI)**	**COE (PV-G-LI-H)**	**COE (PV-W-G-H)**	**COE (PV-W-G-H-LI)**	**COE (PV-W-G-LA)**	**COE (PV-W-G-LA-H)**	**COE (PV-W-G-LI)**	**COE (W-G-LA)**	**COE (W-G-LA-H)**	**COE (W-G-LI)**	**COE (W-G-LI-H)**
Trials	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000	10,000
Mean	0.23	6.07	0.7	7.65	4.36	8.45	0.26	6.86	0.76	0.41	10.83	1.11	12.08
Median	0.21	5.79	0.67	7.32	4.14	8.08	0.24	6.53	0.72	0.38	10.31	1.05	11.55
Standard Deviation	0.15	3.9	0.48	4.88	2.82	5.39	0.17	4.41	0.45	0.27	6.96	0.71	7.7
Variance	0.02	15.24	0.2	23.82	7.96	29.04	0.03	19.43	0.23	0.07	48.46	0.5	59.32
Skewness	0.5931	0.4101	0.3566	0.3799	0.4289	0.3797	0.5873	0.4099	0.3553	0.5947	0.4102	0.3574	0.38
Kurtosis	4.17	3.52	3.28	3.48	3.55	3.48	4.15	3.52	3.28	4.17	3.52	3.29	3.48
Coeff. of Variation	0.66	0.6429	0.6395	0.6376	0.6464	0.6376	0.6591	0.6429	0.6393	0.6602	0.6429	0.6396	0.6376
Minimum	-0.33	-8.35	-1.08	-10.5	-6.03	-11.6	-0.38	-9.42	-1.16	-0.59	-14.88	-1.71	-16.57
Maximum	1.35	30.55	2.67	37.68	22.38	41.6	1.52	34.48	2.87	2.4	54.47	4.21	59.46
Mean Std. Error	0	0.04	0	0.05	0.03	0.05	0	0.04	0	0	0.07	0.01	0.08

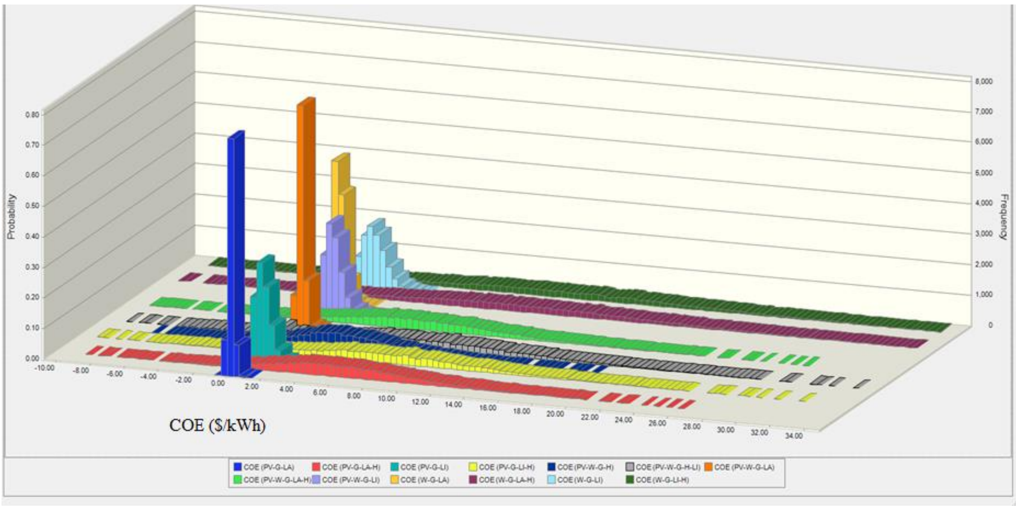


Fig. 9.7: Standard deviation of the combinations

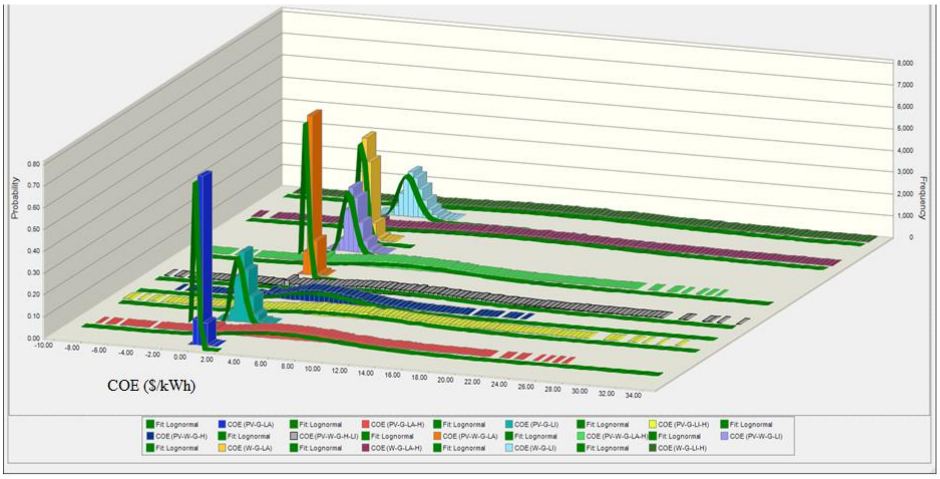


Fig. 9.8: Curve fitting graph

Table 9.5 shows that the minimum standard deviation is obtained in the combination of PV-DG-LA (0.15%). The variance of this combination is 0.02. The combination of PV-wind-DG-LA shows the slightly worse standard deviation (0.17%) as compared to the previous model. The standard deviation is maximum in Wind-DG-Li-ion-hydrogen storage system (7.7%) followed by Wind-DG-LA-hydrogen storage, PV-wind-DG-Li-ion-hydrogen storage and PV-DG-Li-ion-hydrogen storage. Figures 10 and 11 show that the standard deviation of the combination of PV-DG-LA, PV-wind-DG-LA, PV-wind-DG-LA, PV-DG-Li-ion and PV-wind-DG-Li-ion is on the left side of the graph. For the other combinations all are placed in the right hand side of the graph. Therefore, the less risk is obtained for the combination PV-DG-LA as compared to that of the other systems. The certainty of the CRF is shown in Fig. 9.9.

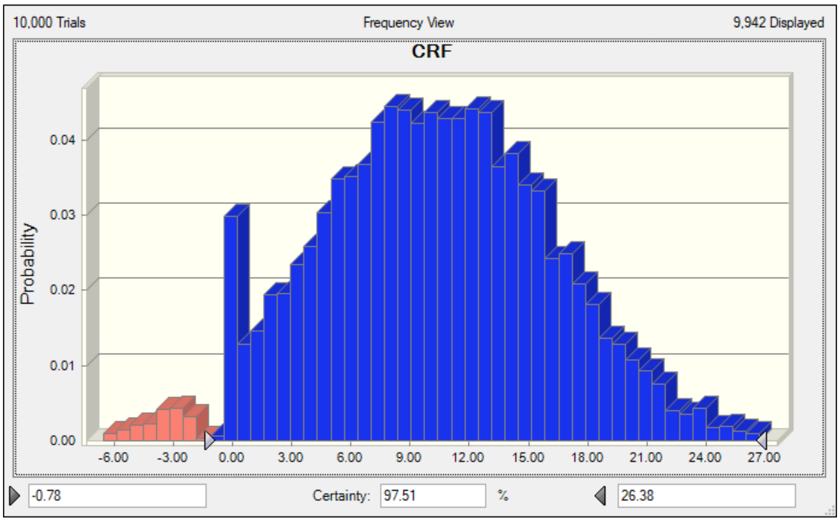


Fig. 9.9: Certainty of CRF

According to Fig. 9.9, the CRF is 97.51% certain which denotes that the analysed economy of the combination is less uncertain. The effects of the economic input parameters on the economy are minimum. Therefore, the systems are economically stable. The impact of the different economic parameters is shown in Fig. 9.10.

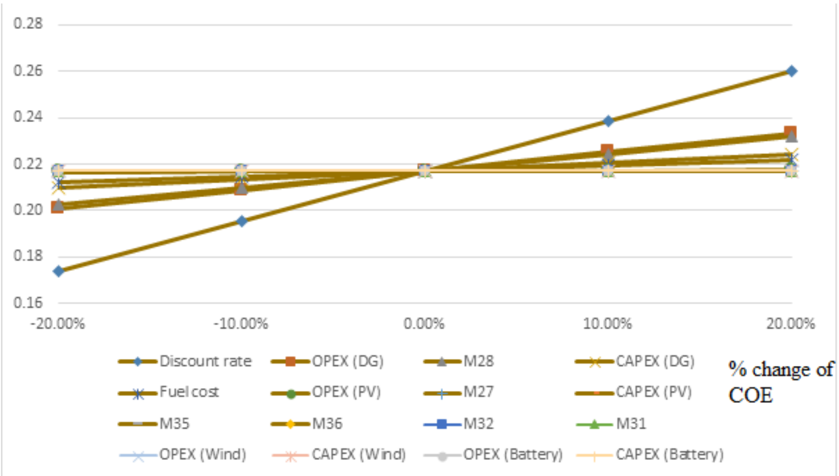


Fig. 9.10: Economic performance impact on COE

Figure 9.10 shows that the impact of discount rate is maximum on the COE of the combinations and it varies between 0.17- 0.25%. The variation of battery capital cost is minimum on the COE of the energy systems followed by the operating cost of the LA storage modules. Hence, the economic risk assessment shows that the PV-DG-LA is the most feasible energy system in terms of uncertainty. However, the techno-economic and low-carbon performance of this combination is not optimum. Therefore, it becomes difficult to decide the optimum energy solution for the study area with respect to technical, economic, low-carbon performance and economic risk assessment criteria. Considering this the MCDM approach is used in this study to decide the 'decided optimum' solution.

9.4.4 MCDM analysis:

To decide the optimum acceptable solution out of alternatives five criteria have been considered. These criteria are distributed under three different categories, i.e., economic, environmental and technical. The COE and NPC are the economic factors, RF is the environmental factor and the F_C is the technical aspect. The values of the criteria for each alternative are shown in Table 9.6. In this study, the TOPSIS MCDM approach is primarily used to decide the optimum solution. The result of TOPSIS analysis is shown in Table 9.7.

Table 9.6: Decision making matrix

Energy combinations	COE ($/kWh)	NPC ($)	RF (%)	F_C (L/year)	Economic Risk
PV-wind-gen-hydrogen storage-Li-ion	0.158	4,24,566	96.8	2,509	5.39
PV-gen-Li-ion	0.159	4,24,568	95.6	2,819	0.48
PV-wind-gen-Li-ion	0.159	4,24,568	96.5	2,628	0.45
PV-gen-Li-ion-hydrogen storage	0.168	4,50,419	96.3	2,720	4.88
PV-wind-gen-LA	0.205	5,51,952	94.3	3,054	0.17
PV-wind-gen-LA-hydrogen storage	0.206	5,52,994	94.4	2,991	4.41
PV-Gen-LA	0.237	6,38,112	93	3,206	0.15
PV-Gen-LA-hydrogen storage	0.238	6,39,154	92.9	3,521	3.9
Wind-gen-Li-ion	0.316	8,49,935	80.5	5, 712	0.79
Wind-gen-Li-ion-hydrogen storage	0.317	8,50,977	80.5	5,712	7.7
Wind-gen-LA	0.35	9,55,341	82.9	4,016	0.27
Wind-gen-LA-hydrogen storage	0.354	9,51,373	82.9	4,016	6.96
PV-wind-gen-hydrogen storage	0.661	1.77M	84.4	3,816	2.82

Table 9.7: TOPSIS analysis result

	Si+	Si-	PI	Rank
PV-wind-gen-hydrogen storage-Li-ion	0.060999	0.132571	0.684873	4
PV-gen-Li-ion	0.04809	0.115467	0.705975	2
PV-wind-gen-Li-ion	0.041716	0.113294	0.730882	1
PV-gen-Li-ion-hydrogen storage	0.05388	0.110172	0.671569	3
PV-wind-gen-LA	0.079863	0.082592	0.508399	5
PV-wind-gen-LA-hydrogen storage	0.085932	0.063129	0.423514	7
PV-Gen-LA	0.088881	0.081266	0.47762	6
PV-Gen-LA-hydrogen storage	0.099965	0.055819	0.358311	9
Wind-gen-Li-ion	0.119822	0.039023	0.24567	11
Wind-gen-Li-ion-hydrogen storage	0.13095	0.024343	0.156756	13
Wind-gen-LA	0.110172	0.05388	0.328431	8
Wind-gen-LA-hydrogen storage	0.125005	0.02846	0.185451	10
PV-wind-gen-hydrogen storage	0.130612	0.033198	0.202663	12

The MCDM analysis is performed by giving the equal weightage to each criterion. The result shows that PV-wind-DG-Li-ion is the optimum solution. To validate the result of the TOPSIS analysis VIKOR MCDM approach is used. The result of the analysis is shown in Table 9.8.

Table 9.8: VIKOR analysis result

	Si	Ri	Qi	Rank
PV-wind-gen-hydrogen storage-Li-ion	0.2	0.2	0.5	5
PV-gen-Li-ion	0.266667	0.1	0.047619	2
PV-wind-gen-Li-ion	0.25	0.1	0.035714	1
PV-gen-Li-ion-hydrogen storage	0.3	0.15	0.321429	3
PV-wind-gen-LA	0.483333	0.15	0.452381	4
PV-wind-gen-LA-hydrogen storage	0.583333	0.15	0.52381	6
PV-Gen-LA	0.533333	0.2	0.738095	7
PV-Gen-LA-hydrogen storage	0.683333	0.2	0.845238	8
Wind-gen-Li-ion	0.8	0.2	0.928571	10
Wind-gen-Li-ion-hydrogen storage	0.9	0.2	1	13
Wind-gen-LA	0.7	0.2	0.857143	9
Wind-gen-LA-hydrogen storage	0.85	0.2	0.964286	11
PV-wind-gen-hydrogen storage	0.85	0.2	0.964286	12
	S*, R*	0.316667	0.15	
	S-, R-	0.75	0.2	

The result of the VIKOR MCDM approach validates the analysis result of the TOPSIS method. Therefore, the optimum solution is PV-wind-DG-Li-ion that meets the required load at a decided optimum economy with an acceptable economic risk. The low-carbon performance of this combination is also better as compared to that of the other solution.

9.4.5 Comparison with existing works:

Several previous studies reported by Akhtari and Baneshi (Akhtari & Baneshi, 2019), Hasan and Genc (Hasan & Genç, 2022), Praveenkumar et al. (Praveenkumar et al., 2022), Akarsu and Genc (Akarsu & Serdar Genç, 2022) and Basu et al. (Basu et al., 2021) mostly focused on hydrogen production from different hybrid energy combinations. The produced hydrogen is used as a secondary utility to meet the local hydrogen demand. However, the practical acceptability of new technologies will depend on economic feasibility including risk associated with ROI. The detailed techno-economic parameters assessment with uncertainties in ROI have not been analysed for this technology in previously reported literature. No prior studies compare this new technology with the conventional electrochemical storage systems with respect to different performance parameters. The analysis result is discussed in the next section.

9.4.6 Techno-economic details of the combinations:

9.4.6.1 Technical assessment:

This section of the study shows the technical details of the optimum solution. The percentage of energy shares from different components are analysed in this study. The result of the evaluation is shown in Fig. 9.11.

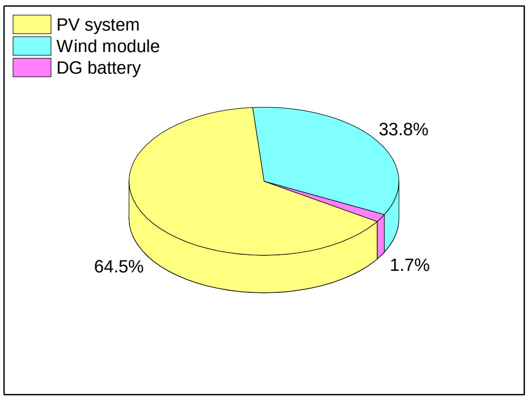


Fig. 9.11: Energy share of the modules

Figure 9.11 shows that the maximum amount of energy is provided by the solar component. The average energy produced by the module is 271685 kWh/yr. The wind module produces 142371.7 kWh/year energy. The rest of the total energy is supplied by the DG set. The amount is only 1.7% and the energy production amount is low. For this reason, the emission from the combination is moderate.

The energy scenario for any one week is analysed and shown in Fig. 9.12.

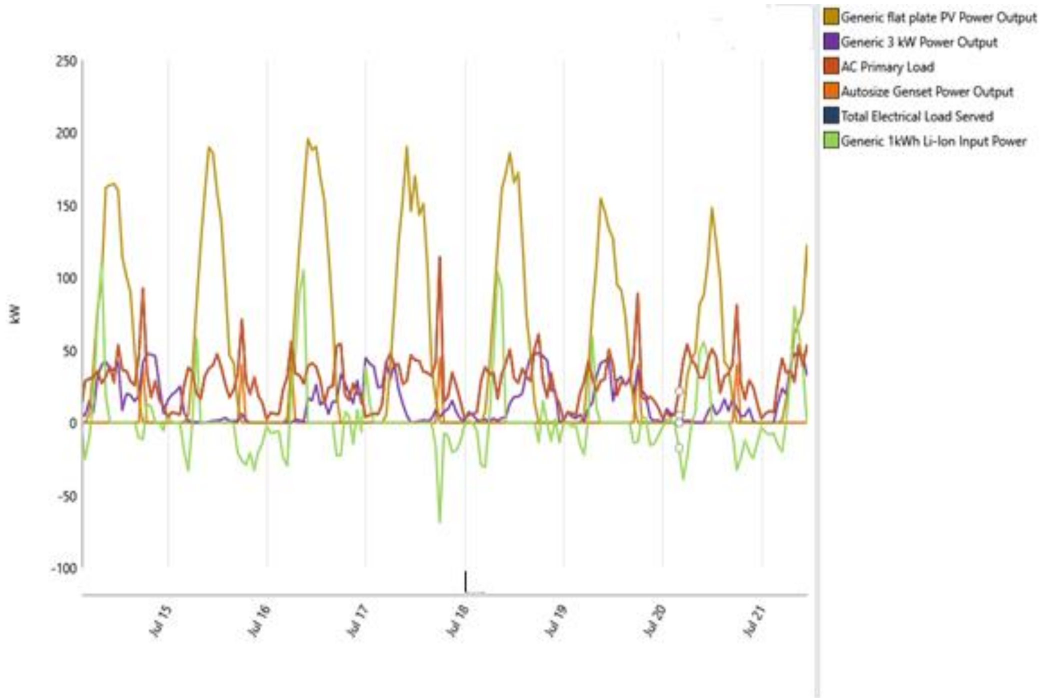


Fig. 9.12: Power share for different modules (for any one week)

Figure 9.12 shows that for any sample one week the maximum load is produced by the solar module, followed by the wind module. The limited amount of energy is supplied by the generator. After meeting the load, the rest of energy is stored in the battery module. The economic assessment of this solution is analysed in the study and discussed in the next section.

9.4.6.2 Economic assessment:

The detailed cost sharing of the components is shown in Table 9.9.

Table 9.9: Cost share of the components

	Autosize Genset	Generic 1kWh Li-Ion	Generic 3 kW	Generic flat plate PV	System Converter
Capital	40,000.00	96,300.00	31,680.00	22,945.65	46,604.75
Replacement	0	54,535.09	7,264.94	8,952.68	20,217.50
O&M	13,307.62	50,565.19	2,520.38	3,804.73	10,310.91

Fuel	47,419.44	0	0	0	0
Salvage	-6,915.32	-11,367.38	-4,495.37	-5,539.69	-4,587.22

According to Table 9.9, the capital cost is maximum for the storage module followed by that of the converter, diesel generator, wind module and flat plate PV. The replacement cost is maximum for the storage module. This module also shares the maximum portion in O&M cost. The fuel cost due to the DG module is $47,419/yr. All the components share the salvage cost. The maximum salvage cost is shared by 34% by the storage modules followed by the generator module (21%), PV module (16.83%) and converter (13.9%). The least salvage cost is obtained from the wind module.

Therefore, the optimum energy combination of PV-wind-DG-Li-ion is the acceptable solution to meet the load demand of the area at the decided best economy and investment risk combined with low-carbon power generation.

9.5 Summary of the Chapter:

The study assessed techno-economic performance aspects with financial risk analysis for 'green' hydrogen with conventional electro-chemical storages. A MCDM method finally decide an acceptable optimal solution in terms of overall sustainability aspects. The techno-economic optimization analysis shows that the combination of PV-wind-DG-hydrogen storage-Li-ion is an optimal (COE-$0.158/kWh, NPC-$4,24,566, and F_C–2509L/year) solution. The RF is also high for this combination. However, the risk in ROI for this combination is high. On the other hand, the financial risk is less for PV-DG-LA energy combinations but it is not techno-economically optimal. The RF is also less. The decision-making approach helps to obtain the practically acceptable feasible solution which is techno-economic with moderate RF and risk in ROI. The analysis result shows that the combination of PV-wind-DG-Li-ion is the accepted optimal solution with COE-$0.159/kWh, NPC - $4,24,568, Fc- 2628L/year, RF- 96.6%, and std. deviation – 0.45%. The study shows that hydrogen storage may be techno-economically feasible but the risk in ROI is high and that makes the combination economically unstable. Hence, the conventional electro-chemical storage is more stable as compared to the new option for the decentralized hybrid energy system.

Chapter-10

Techno-economic optimization of integrated renewable power and desalination*

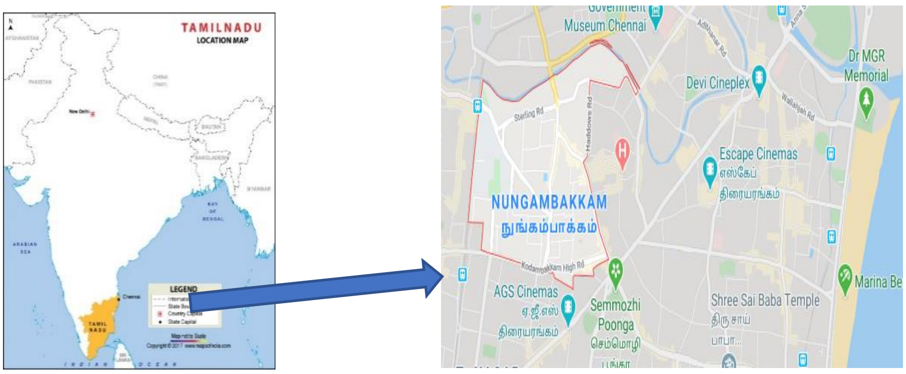
(***Das, S.**, Ray, A., De, S.* (2022): Techno-economic optimization of desalination process powered by renewable energy: a case study for a coastal village of southern India. **Sustainable Energy Technologies and Assessments (Elsevier) (Published).** DOI: https://doi.org/10.1016/j.seta.2022.101966)

10.1 Objective of the work:

The analysis compares different desalination system supplied by the locally available renewable resources to mitigate the energy demand of the desalination process in Indian scenario. Hence, the study proposed the optimal desalination unit with the feasible energy resource combinations that produces the fresh water for the study area at minimum economic and environmental degradation. To meet the energy demand, in this analysis, the locally available renewable resources such as PV, wind are studied. The storage devices are attached with these renewable resources to attain the peak load demand. The diesel generator (DG) set is used if the renewable resources and storage devices fails to attain the demand. A coastal villages of Chennai, south eastern state of Chennai, India is selected for this analysis (NASA, 2018).

10.2 Study area details:

Several states of India such as Tamil Nadu, Kerala, West Bengal, and many others are facing water crisis (NITI Aayog, 2018). This study area is a medium-size village located in Thiruvallur Taluk of Thiruvallur district, Tamil Nadu and the inhabitants of the area are facing severe water crisis. The latitude and longitude of this area are 13.0654°N, 80.2326°E. Figure 10.1.a shows the study area location in Indian map, and 10.1.b shows the demographic view (Rai, 2020).



(a) (b)

Fig. 10.1. a) Selected study location in Indian map, b) demographical enlarge view (Rai, 2020)

10.3 Materials and Methodology:

This study analyses three different desalination techniques namely multi-stage flash (MSF), multiple-effect desalination (MED), and one membrane desalination reverse osmosis (RO) along with the locally available renewable energy combinations required as inputs to this process to determine an optimum solution for minimum cost and emission.

10.3.1 Desalination methods:

The available desalination techniques are:

A: **Thermal desalination process:** - Multi-Stage Flash (MSF) and Multi-Effect distillation (MED) are the primary thermal desalination processes.

B: **Membrane desalination: -** Reverse Osmosis (RO) is the main membrane-based desalination process.

In this study, these three types of desalination techniques are analysed.

Multi-Stage Flash (MSF) is one of the thermal desalination units, which desalinates seawater through several stages. Initially the temperature of the water is increased nearly to the boiling point (approximately 90 Ċ- 110 Ċ) and the pressure of the water is then reduced at several stages. Part of the water evaporates, i.e, at each stage it is distilled. The remaining saline water is relocated to the next stages of evaporation again. At the end of these several stages, the freshwater is produced by the process of distillation of water (Hemmati et al., 2016; Kim, 2011). The process can desalinate 0.2 upto 17 MIGD of salty water (Nannarone et al., 2017). Electrical energy is required to run the pump which is used to send the saline water into the condenser. In this section water is pre-heated and then it is passed through several chambers and then to the boiler to evaporate the water again. This requires thermal energy. So, both electrical and thermal energies are required for this desalination process.

Multi-effect distillation (MED) is also considered as a thermal desalination technique. This is also carried out in several stages. The main difference of MED with MSF is that in the next stage the generated steam gets condensed and then again evaporated and distilled (Ghobeity & Mitsos, 2014). Figures 10.2 and 10.3 show the MSF and MED processes.

Irrespective of these two thermal desalination processes, membrane desalination is also considered as one of the major seawater desalination techniques. Reverse Osmosis (RO) is the primary membrane desalination technique by which fresh water is produced from the saline water. By using high-pressure pumps feed water passes through the semi permeable membrane at osmotic pressure and is delivered as potable water (Curto et al., 2021). The impurities are concentrated into reject stream and flush it into drain or sea. The material of this process is prepared with cellulose acetate, polyamides etc (Garud et al., 2011). This membrane comprised of hollow fiber, and for water treatment spiral wound is used based on the water composition and the operation parameters of the plant (Alkaisi et al., 2017; S. Lee et al., 2019). The RO process is shown in Fig. 10.4. For all the above-mentioned system the brine discharge commonly deposited to the seawater (Missimer & Maliva, 2018).

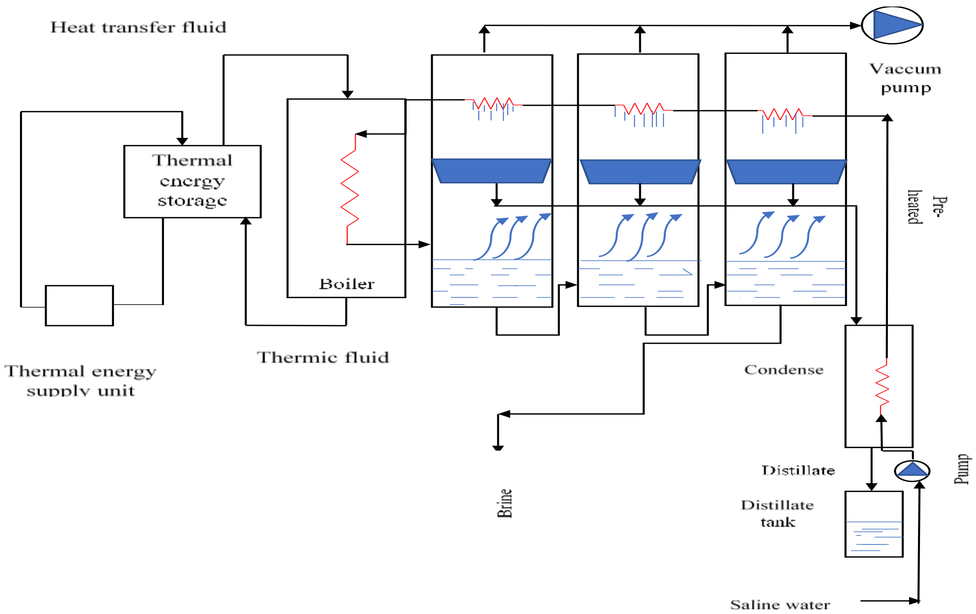


Fig. 10.2: MSF desalination method

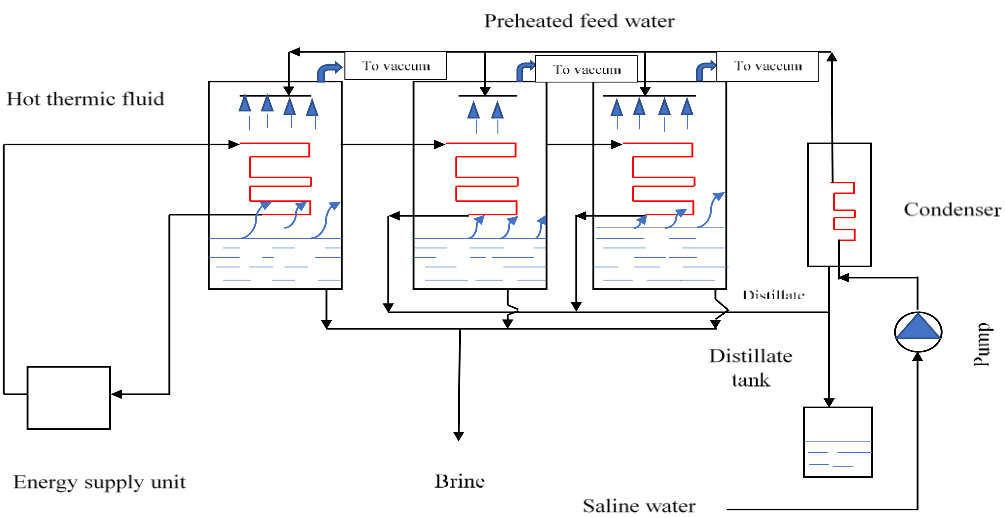


Fig. 10.3: MED desalination system

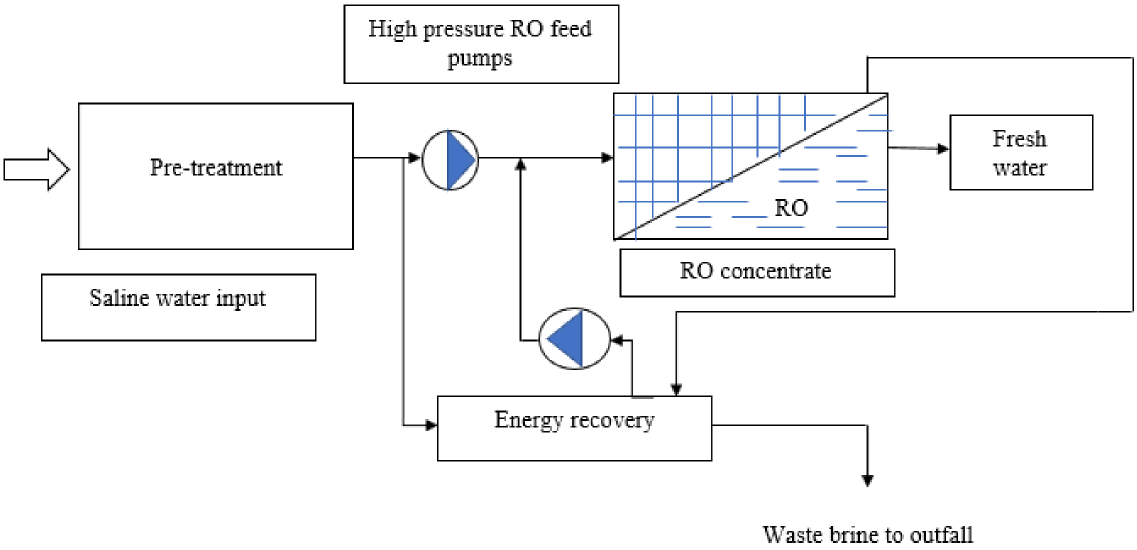


Fig. 10.4: RO desalination system

10.3.2 Desalination unit energy requirements:

The MSF desalination technique consumes 3 kWh/m^3 of electrical energy as well as 14 kWh/m^3 of thermal energy (Lindemann, 2004). Similarly, the MED method also consumes 1.5 kWh per cubic m of electrical and 10 kWh per cubic m of thermal energy respectively (Abdelkareem et al., 2018). However, the RO process is membrane-based. This process demands 3 kWh/m^3 of electrical energy for desalination (Shemer & Semiat, 2017).

In this analysis, locally available renewable resources such as solar and wind are considered as renewable resources. A storage system mainly battery is attached to overcome renewable energy resources intermittency. The battery connected renewable system lacks to attain the energy requirement, a DG (diesel generator) sets will begin to operate to supply the auxiliary energy requirement for the necessary time being.

10.3.2.1 Solar PV modeling:

The output power of the PV module is discussed in equations shown in Table A. 1, Sl. No.: 1, Eqs. i-iii (Babatunde et al., 2022; Emad et al., 2021; Mandal et al., 2018) in Supplementary Index (SI).

To pursue the analysis, a monocrystalline flat-plate PV module is used. The horizontal axis maximum power point tracking (MPPT) system is integrated with this module. The installation cost, cost of replacement and operation and maintenance (O&M) cost is discussed in Table 10.1 (Nag & Sarkar, 2018).

10.3.2.2 Wind turbine modeling:

The output power of the wind module is discussed in equations shown in Table A. 1, Sl. No.: 2, Eqs. i-iii (Emad et al., 2021) in SI.

This analysis is assumed to use a 3kW wind turbine model. The considered technical and economic description of the module are provided in Table 10.1 (Nag & Sarkar, 2018).

10.3.2.3 Diesel generator (DG) modeling;

The equation of DG system is discussed in Table A. 1, Sl. No.: 5, Eq. i in SI (Ramesh & Saini, 2020).

In this study, the useful life of DG set is considered as 15000 h. The technical and economic specifications of DG module are provided in Table number 10.1 (Khalid et al., 2017).

10.3.2.4 Storage modeling:

The equations of storage systems are discussed in Table A. 1, Sl. No.: 4, Eqs. i-v in SI (Baneshi & Hadianfard, 2016).

In this study Lead-acid (LA) battery is used. The power and energy storage capacity of this battery are high. It is also quite fast in charging and discharging. It causes almost no pollution and is easy to install also with lesser operational cost (Krishan & Suhag, 2019). Values of different relevant technical and economic parameters are shown in Table 10.1.

10.3.2.5 Converter modelling:

The equation of the converter system is discussed in Table A. 1, Sl. No.: 6, Eq. i in SI (Emad et al., 2021).

The detail technical and other specifications of this component are provided in Table 10.1 (Nag & Sarkar, 2018a). The overall layout by using these energy resources is shown in Fig. 10.5. In the AC bus wind turbine and diesel generator have been connected and with the DC bus solar cell and storage systems are connected. The red and blue lines denote the thermal and electrical energy flows. As the power demand is conventional AC, so the electrical load is connected to the AC bus system. The amount of thermal energy needed is based on the type of desalination process used. The heat may be supplied from a fossil fuel powered boiler or from the waste heat of the diesel generator set.

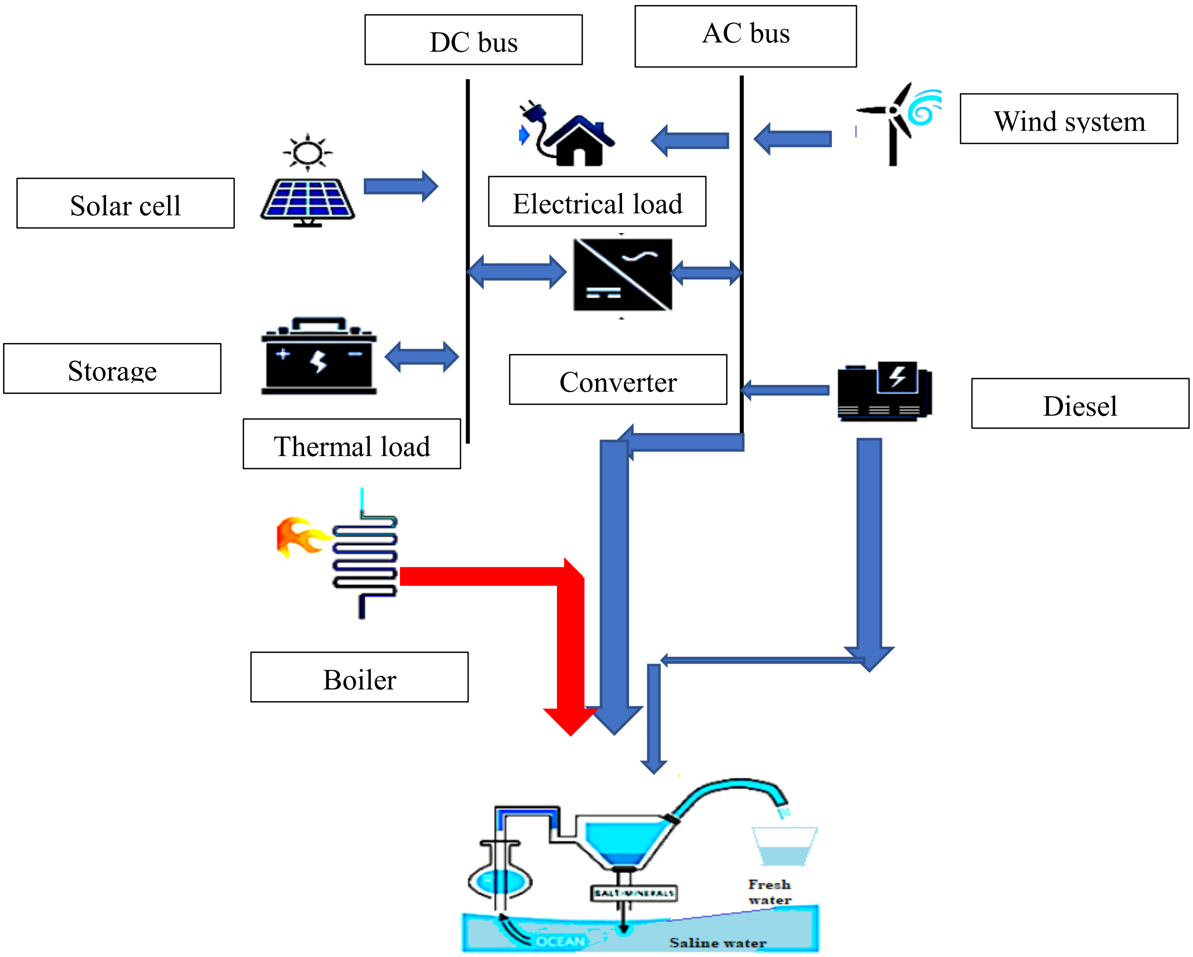


Fig. 10.5: Schematic Diagram

Table 10.1: Energy components specifications (Krishnan &Suhag, 2019; Nag & Sarkar, 2018; Khalid et al., 2017)

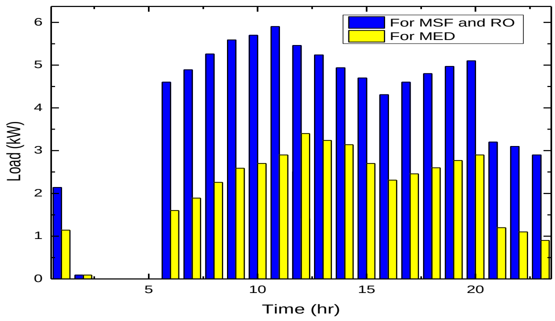
PV module (Monocrystalline flat plat)-(LR6-60HV)		**Wind turbine module**		**Battery**		**System converter**		**DG set**	
System identifications	Value	System identifications	Value	System identifications	Value	System identifications	Value	System identifications	Value
Operating Temp.	47 °C	Rated capacity	3 kW	Nominal voltage	12 V	Inverter efficiency	95%	Capital cost	($/kW) 742
Efficiency	18.3%	Graded wind speed	12 m/sec	Nominal capacity	3.12 kWh	Rectifier efficiency	95%	Replacement cost	($/kW) 742
Derating Factor	80%	Cut-in speed	3.4 m/sec	Maximum capacity	260 Ah	Inverter lifetime	15 year	O&M cost	($/kW/hour) 0.04
Temperature co-efficient	-0.410	Cut-out speed	25 m/sec	DoD	60 %	Rectifier relative capacity	100 %	Life time (hours)	15000
Ground reflection	20%	Hub height	17 m	Roundtrip efficiency	85 %	Initial cost ($/kW)	465	Diesel fuel price	($/L) 1
V_{OC}	47.5 V	Initial cost ($/kW)	1200	Initial cost ($/kW)	350	Cost of replacement ($/kW)	465	Fuel curve intercept	0.671 L/hour
I_{SC}	9.64 amp	Cost of replacement ($/kW)	1200	Cost of replacement ($/kW)	300	Yearly cost of operation and maintenance ($/kW/year)	9	Slope of fuel curve	0.236 L/hour/kW
Lifetime	25 years	Yearly cost of operation and maintenance ($/kW/year)	18	Yearly cost of operation and maintenance ($/kW/year)	10				
Initial cost ($/kW)	1667	Lifetime	20 years	Life time in year	10				
Cost of replacement ($/kW)	1667	Output type	AC						

Yearly cost of operation and maintenance ($/kW/year)	10	Temperature effect	No

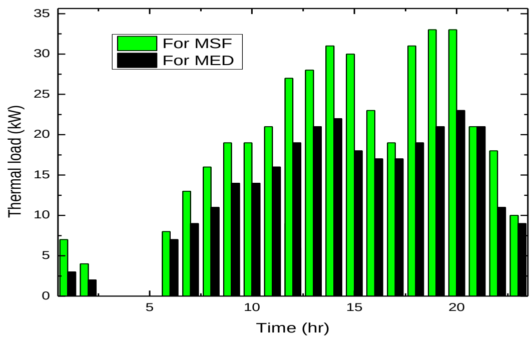
10.3.3 Input assessment:

10.3.3.1 Load assessment:

According to the literature, 20 L/day freshwater is needed by each person. As the population is 1500, the total water demand for this area is 30 m^3/day (Chandramouli, 2011; Kashmir, 2001). For the MSF desalination, the thermal energy required is 420kWh/day and the electrical energy required is 90 kWh/day. Again, for the MED desalination the thermal energy required is 300kWh/day and the electrical energy required is 45 kWh/day (Franzitta et al., 2016). RO is a membrane-based system it demands only electrical energy of magnitude 90 kWh/day. The thermal and electrical load curves are shown in Fig. 10.6.



(a)



(b)

Fig. 10.6: load assessment (a) electrical (b) thermal

10.3.3.2 Solar and Wind resource data:

For the selected study area, the locally available renewable resources are solar irradiation and wind speed. In this area wave, tidal and other renewable resources are not properly developed (IRED, 2014). Hence, the data of these two resources are obtained from the NASA weather report (NASA, 2020). The temperature data of that study area is collected from the NASA weather report. Figure 10.7 is the graphical representation of these data.

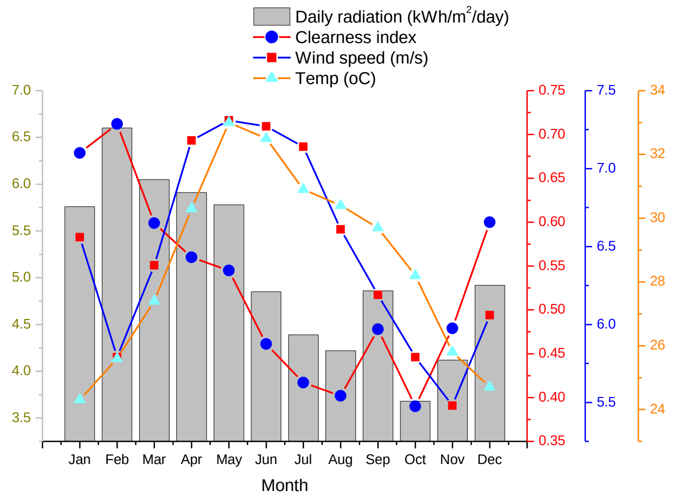


Fig. 10.7: Resource data (NASA, 2020)

According to Fig. 10.7, solar radiation varies between 4-6.6 kWh/m^2/day. The wind speed varies between 5.5-7.5 m/s.

10.3.3.3 Economic assessment:

To evaluate the economic feasibility of the hybrid energy model a few parameters are considered in this study. The considered parameters are discussed below.

10.3.3.3.1 Cost of electricity (COE):

The COE is shown in Eq. i, in Table A.2, Sec. 2.ii of SI.

10.3.3.3.2 Net Present Cost (NPC):

The NPC is shown in Eqs. i-iii, in Table A.2, Sec. 2.i of SI.

10.3.3.3.3 Operation and maintenance (O&M) cost:

The O&M cost is shown in Eq. i, in Table A.2, Sec. 2.iv of SI.

The penalty cost for the capacity shortage and the carbon emission penalty costs are shown in Eqs. i-ii, Sec. 2.v in Table A.2 of SI.

10.3.3.3.4 Cost of Water (COW):

The calculation of COW is shown in Eq. i, Table A.1, Sec. 2.vi (SI) (Gökçek & Gökçek, 2016).

For this analysis the tank cost is considered as $ 20,000 (Gökçek, 2018).

10.3.3.4 Objective functions:

A global objective function is developed based on the selected project variables and constraints. The target of this optimization is to find the optimum economic option using localized energy resources to attain the energy demand out of all the possible various feasible simulated options. The defined objective function is shown in Eq. 10.1 (Ma et al., 2018),

$$Function = \min(\sum_{i=1}^{I} CI.N_C + \sum_{i=1}^{I}\sum_{j=1}^{J} C_{O\&M}.N_c + \sum_{i=1}^{I}\sum_{j=1}^{J} C_{rep}.N_c + \sum_{i=1}^{I}\sum_{j=1}^{J} C_{diesel}.N_c \quad (10.1)$$

According to Eq. 17 the CI represents the initial expenditure, $C_{O\&M}$ represents the system's O&M cost, C_{rep} represents the system's cost of replacement, C_{diesel} represents the fuel expense. The unit of these expenses are in US$. N_c represents the capacity of the individual apparatuses in kW.

10.3.4 Description of Process:

These feasibility of the designed systems and economic reports are generated from HOMER®. It optimizes the financial (COE, NPC and O&M cost) as well as the emission (greenhouse gas (GHG), renewable fraction (RF)) aspects of the energy options on the basis of given inputs. In the next stage, these output constraints used for the MCDM analysis. The TOPSIS-MCDM technique is considered for this study. The methodology of this study is described in a flowchart shown in Fig. 10.8.

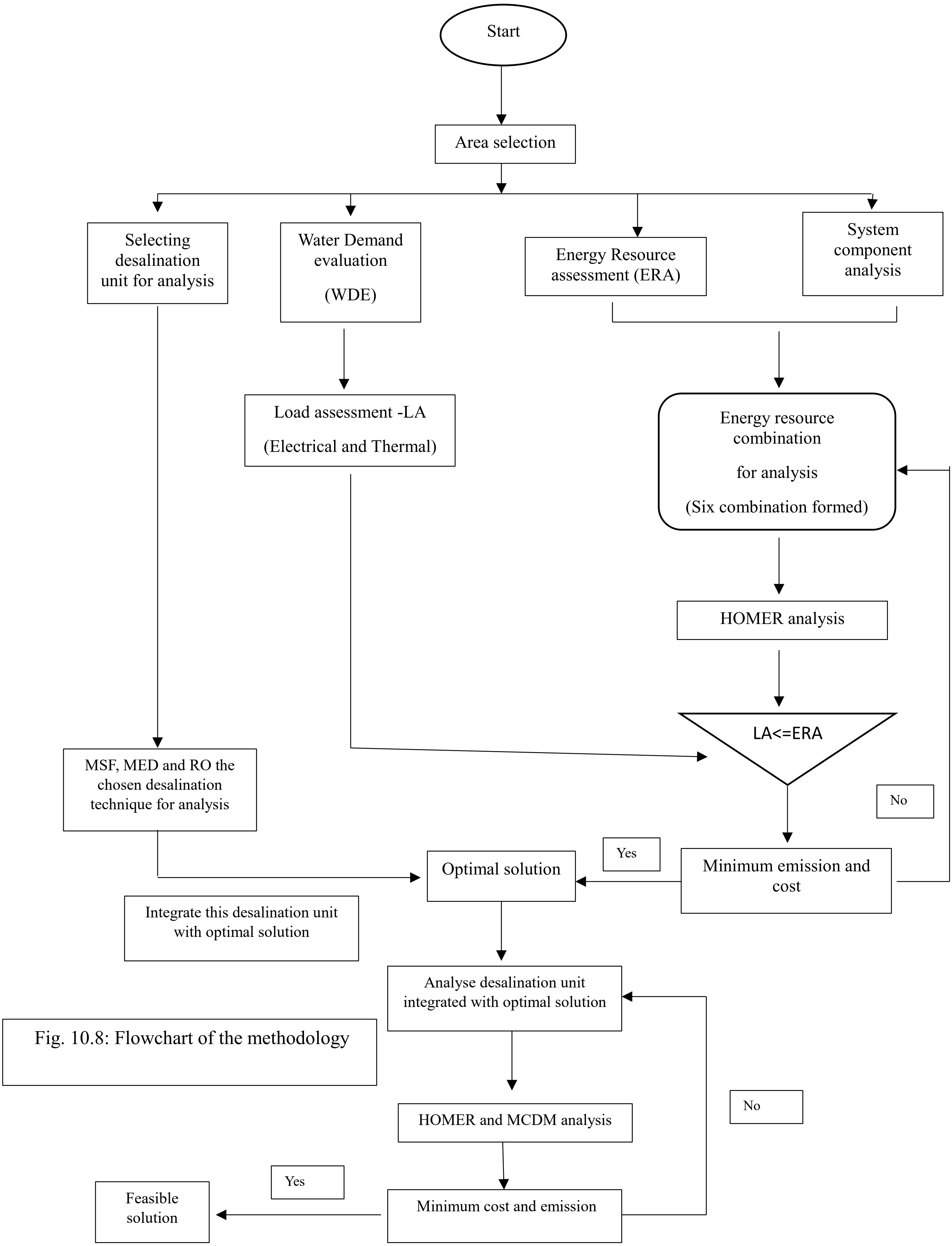


Fig. 10.8: Flowchart of the methodology

10.3.4.1 HOMER® methodology:

The detailed working principle of HOMER® is shown in discussed in Chapter 5, in “Sec. 5.3.3.1: HOMER® methodology” (Ramesh & Saini, 2020).

10.3.4.2 MCDM method:

The optimal solution is selected by using multi-criteria-decision-making (MCDM) method (Diemuodeke et al., 2019; Lozano-Minguez et al., 2011). In this analysis, the TOPSIS is considered. The result is decided on the basis of selected attributes such as technical, economic, and emission.

10.3.4.2.1 TOPSIS technique:

The details of the TOPSIS-MCDM method are discussed in Chapter 5, in “Sec. 5.3.3.2.1: TOPSIS-MCDM algorithm”.

10.4 Results and Discussion:

The analysis objective to find the optimal seawater desalination process out of three desalination techniques, viz., MSF, MED, and RO powered by locally available hybrid renewable resources.

10.4.1 Energy resource analysis:

Primarily, all possible energy resource combinations are simulated based on the input constraints and ranked the output from the minimum NPC to the maximum NPC. This study analysed six possible energy resource cases discussed in Table 10.2 for providing energy to the desalination system. These cases are analysed for each of three-desalination units considered in this study. The optimal combination is chosen based on the performance indicators such as COE, NPC, O&M, GHG, RF, and unmet load (UL). The result of this comparative study is shown in Figs. 10.9-11. Figures 10.9-11 show the comparative study of all six cases considered in this analysis for MSF, MED, and RO respectively. All the values are normalized between 0-1 for better comparison on the same scale. The project lifetime is considered as 20 years.

Table 10.2: Possible energy resource combination

Sl No.	Case	Combination type	Resources
1	case 1	Non-renewable	Generator - battery
2	case 2	Renewable + non-renewable	PV-generator -battery
3	case 3	Renewable	wind - battery
4	case 4	Renewable + non-renewable	wind – generator- battery
5	case 5	Renewable	PV-wind-battery

6	case 6	Renewable + non-renewable	PV-wind-generator-battery

According to Figs. 10.9-10.11, it is observed that for each of these three desalination scenarios hybrid systems consisting of PV-wind-battery and DG (case 6) is found to be feasible energy resource options with respect to the techno-economic and environmental performance indicators. In these figures, it is noticed that the normalized value of economic performance indicators like COE, NPC and O&M and the ecological performance indicators like GHG, RF for the above-mentioned hybrid system is least as compared to other cases. It is followed by a wind-generator battery system (case 4). The fully renewable energy resources like case 3 (Wind-Battery system) and case 5 (PV-Wind-Battery system) are not considered as a suitable option due to the presence of high unmet load and also the COE is higher than case 6. The other two cases like the generator system (case 1) and PV-generator system (case 2) emitted high GHG and also the COE, NPC, and O&M are high for these two cases. So, these cases are also not suitable for providing energy to the water desalination system. This suggested that hybridization is the necessary requirement to provide energy to this system and in this case study PV-wind-battery-generator is a feasible hybrid energy resource combination. From the analysis, it is observed that hybrid renewable energy resource combination is considered as a suitable power resource option for each desalination plant rather than supplying power through a diesel generator. This reduces the cost of water and also minimizes the environmental impacts.

Fig. 10.12 shows that the cost of water (COW) is minimum for the PV-wind-generator-battery-based hybrid system. For each of the desalination units, the COW is a minimum when these are integrated with the selected hybrid system. The COW values are approximately \$4.57/m^3 for MSF, \$4.41/m^3 for MED and \$4.57/m^3 for RO. These are the least COWs with respect to the other energy resource options. The COW value is a maximum for the generator-based system (viz., \$5.19/m^3 for MSF, \$4.91/m^3 for MED and \$5.19/m^3 for RO) and is steadily decreased by including a renewable resource for the energy mix. It is also the minimum for the PV-wind-generator-battery system. Though the generator is used in this system as an alternative resource, limited usage of it reduces the COE and COW values simultaneously. For this case, GHG emission is also lesser than that for other energy resource options, specifically for generator based standalone systems.

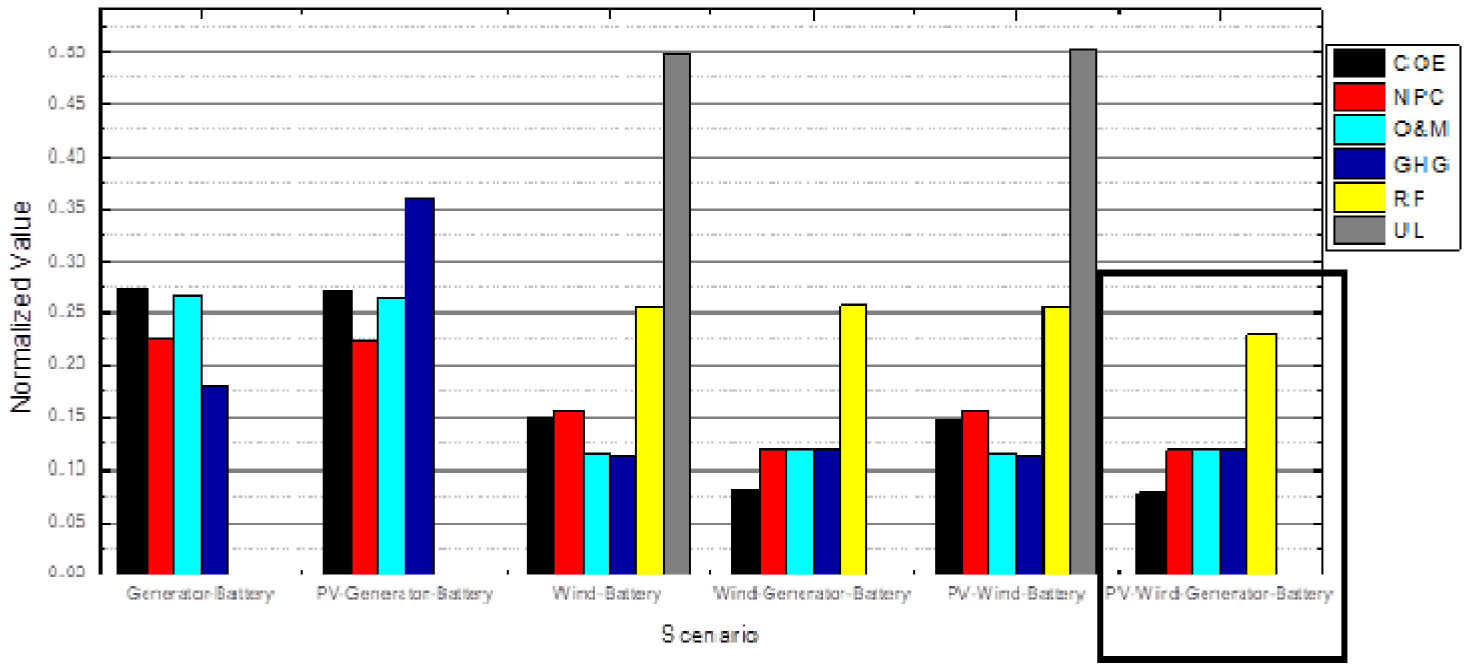


Fig. 10.9: Scenario Analysis for Multi-stage flash (MSF)

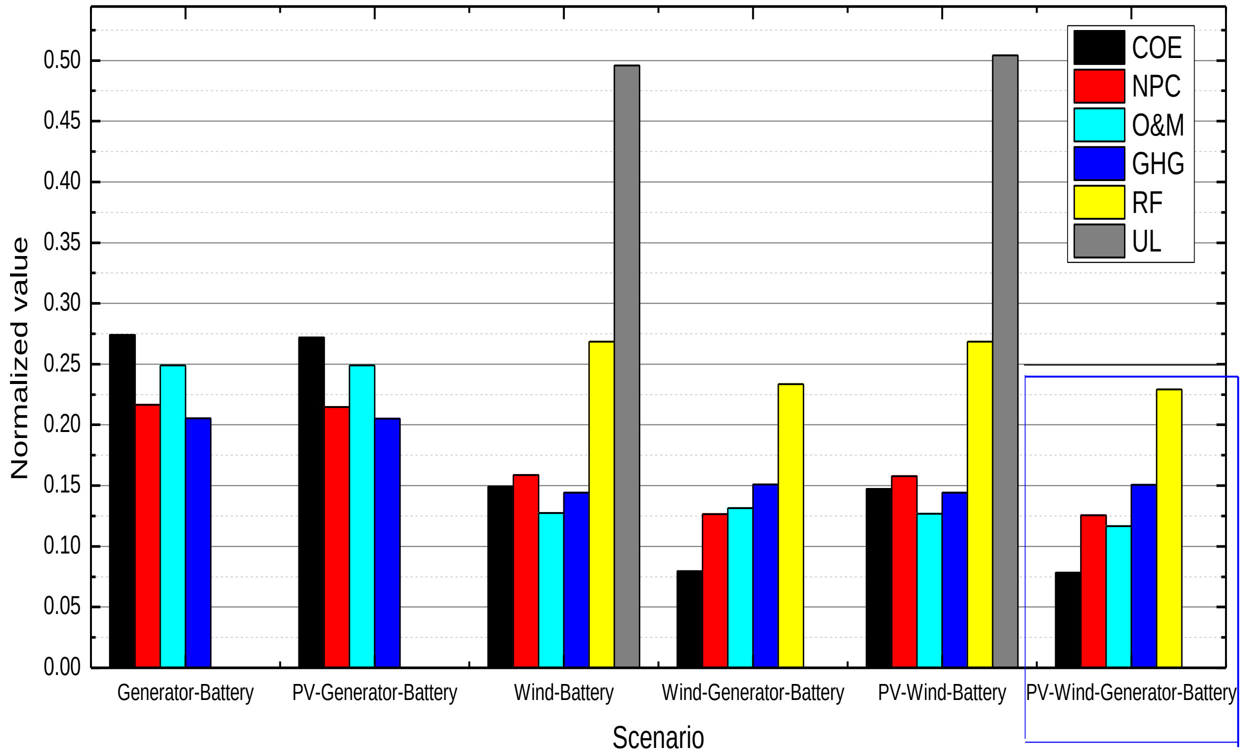


Fig. 10.10: MED scenario analysis result

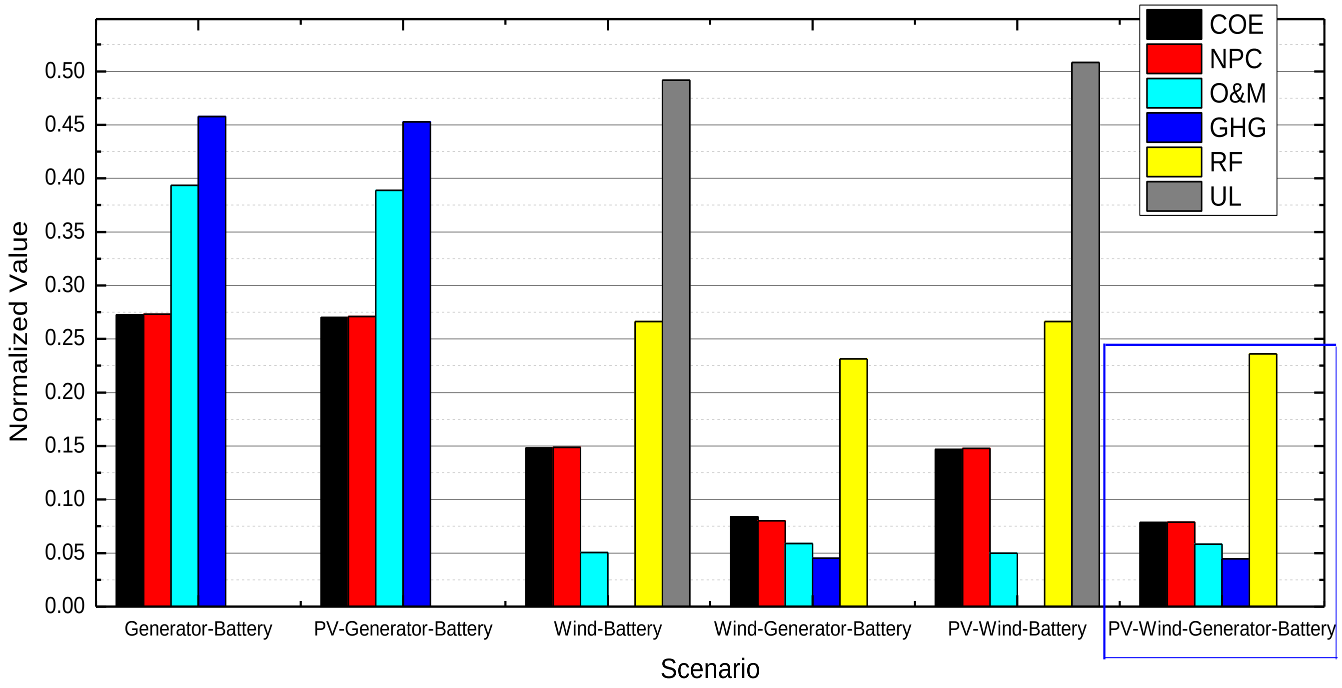


Fig. 10.11: RO scenario analysis

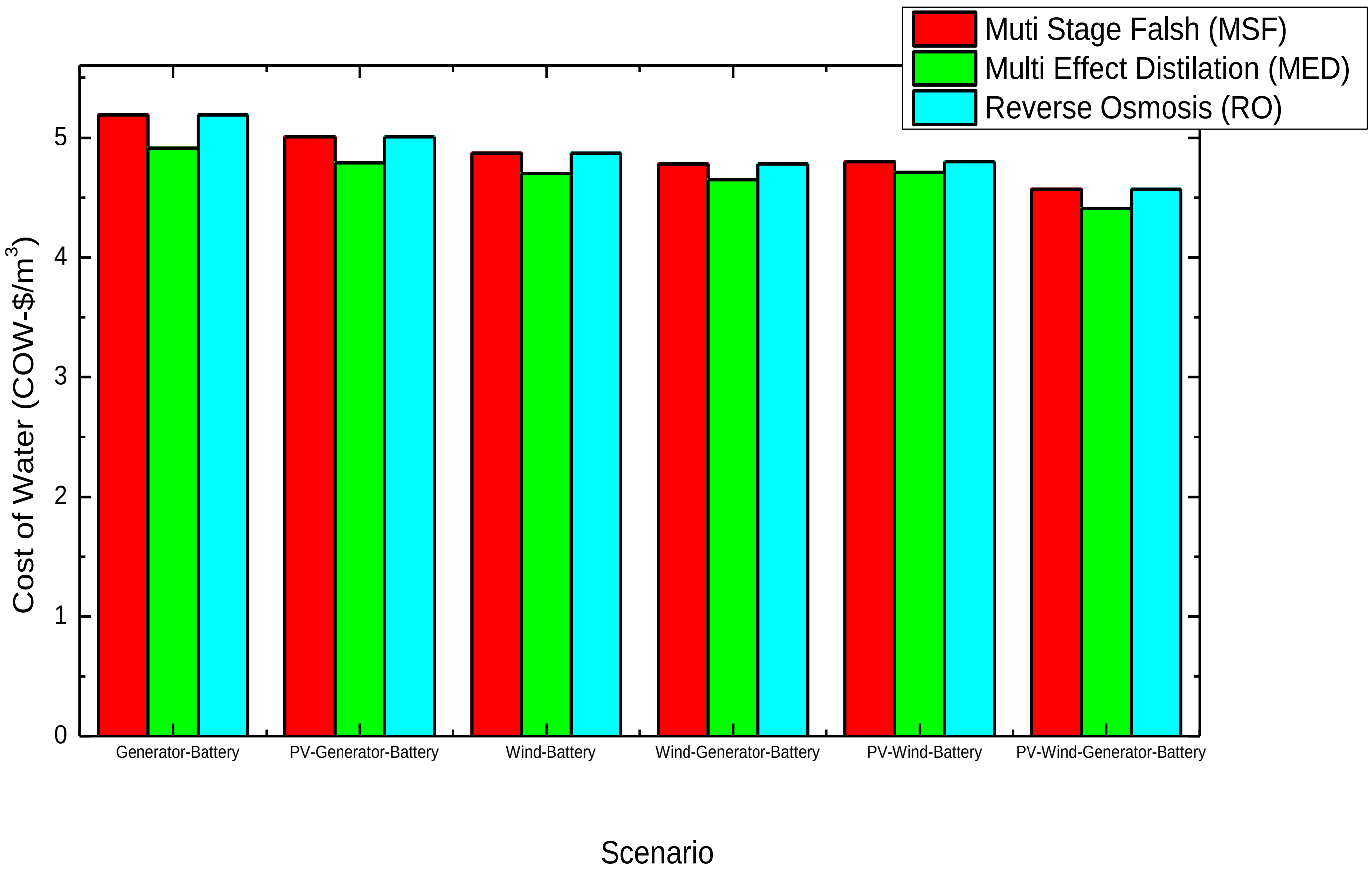


Fig. 10.12: Cost of Water (COW- $\$/m^3$) in different hybrid scenario for each desalination

After this energy resource investigation, it is essential to find the feasible desalination unit for this study area that is able to mitigate the local water crisis at minimum cost and GHG emissions. Therefore, three considered desalination units (i.e., MSF, MED, and RO) are analysed by integrating the energy options (PV-wind-generator-Battery). This analysis is done by using both the HOMER® simulation and the MCDM approach. In the second step, this analysis is done.

10.4.2 Desalination technique selection:

The comparative study is done mainly on the basis of economic constraints such as COE, NPC, and O&M and environmental constraints like GHG emission and RF. The values of these chosen constraints are obtained from the HOMER® analysis. These values are shown in Table 10.3. By using values of these constraints, the selection of optimal desalination units for the locality is done.

Table 10.3: Desalination unit's constraints value

	Economic constraints				Environmental constraints	
Desalination unit	COE ($/kWh)	COW ($/m^3)	System NPC in $	O&M cost ($/year)	Emitted GHG (kg/year)	RF (%)
Multi stage flash (MSF)	0.334	4.57	344793	23936	51462	15.7
Multi Effect distillation (MED)	0.33	4.41	218356	16395	36615	11.1
Reverse Osmosis (RO)	0.334	4.57	127114	5240	2930	88.7

Table 10.3 shows that the COE and COW are least for the MED desalination technique (i.e., $0.33/kWh, and $4.41/m^3) with respect to other two desalination techniques analysed in this study. The COEs and COWs for MSF and RO are approximately $0.334/kWh and $4.57/m^{3}respectively for the both. In spite of the higher COE the other constraints such as NPC, O&M, and GHG are the least in the RO system as shown in Table 3. The NPC, O&M, and GHG values for the MSF and MED desalination techniques are ($ 344793 and $ 218356), ($23936/year and $16395/year), and (5146 kg/year and 36615 kg/year) respectively. Also, RF percentage value is high for the RO system as compared to the MSF and MED techniques. This increases the GHG emission rates of the MSF and MED processes as compared to the RO process.

Thus, based on the HOMER® analysis only, it is difficult to conclude the optimal desalination process for the village. This situation demanded to introduce the MCDM approach to find the optimal feasible desalination process out of these three desalination processes. The TOPSIS algorithm is used as a decision-making approach for finding the optimal desalination unit to supply potable water to the locality. The decision is made based on the TOPSIS approach and the analysis result is shown in Table 10.4.

Table 10.4: Relative distance and performance ranking calculation

Types of desalination	$S_i^+ + S_i^-$	Performance Score $C_i = \frac{S_i^-}{S_i^+ + S_i^-}$	Ranking
MSF (Multi Stage Flash)	0.279594	0	3
MED (Multi effect distillation)	0.285911	0.398925	2
RO (Reverse Osmosis)	0.281324	0.993831	1

According to the TOPSIS algorithm as shown in Table 10.4, the RO process secured the highest score followed by the MED and MSF. According to this algorithm RO holds the top rank (rank 1) followed by MED (rank 2) and MSF (rank 3).

Thus, through MCDM analysis RO desalination technique emerges as the best feasible desalination process for the selected study area. This RO desalination process with the integration of a hybrid energy option (PV-wind-generator-battery) is the optimal feasible solution to supply potable water to this location by minimizing both cost and environmental degradation. The detailed examination of this system is discussed in section 10.4.3.

10.4.3 Detailed analysis of the optimal desalination process:

In this section, the detailed techno-economic and environmental analyses are reported for the optimal desalination unit.

The detailed assessment of this system is focused on analysing the techno-economic and environmental performance of the combined energy solution. Table 10.5 shows the individual components of the combined energy solutions capacity. The economic factors such as COE, NPC, and O&M for each of these components are also shown in Table 10.5.

Table 10.5: Component detail architecture and economic analysis

Component		NPC ($)	COE ($/kWh)	O&M ($/year)	Rated Capacity	Capacity factor (%)	Minimum Output (kW)	Average production amount (kW)	Maximum production amount (kW)	Overall production amount (kWh/year)
		Economic Assessment				**Technical Assessment**				
PV panel		526	0.11	5.72	0.295 kW	15.9	0	0.047	0.246	10411
Wind Turbine		33802	0.0151	432	72 kW	30.6	0	22.1	72	183282
Diesel Generator		38906	0.242	1622	12 kW	3.24	3	11.3	12	3714
Converter	Inver	5363	0	72.3	8.03 kW	7.99	0	0.686	7.76	0
	Recti					9.78		0.839	8.59	
Battery		48181	0.0755	700	71.8 kWh	-	0	18	26	0

Table 10.5 shows that the wind turbine module is the primary device of this hybrid system with the yearly energy production of approximately 183282 kWh/year followed by the PV module with an energy production of 10411 kWh/year and the diesel generator with the yearly energy production of 3714 kWh/year. The capacity factor is high for the wind turbine (approximately 30%) and least for the diesel generator (approximately 3%). Due to the environmental impact of the diesel generator, it is only used to meet the gap between electricity demand available supply from the renewable devices, i.e., the wind turbine and the PV unit. In COE, the contribution of the diesel generator is maximum (approximately \$0.242/kWh) followed by that of the PV module (\$0.11/kWh) and battery system (\$0.0755/kWh). The wind turbine module has the least COE contribution (\$0.0151/kWh). Similarly, the battery storage is the major contributor (approximately \$42181) for the NPC of the system and the PV module is the least contributor (approximately \$526). Diesel generators are the primary contributors to the O&M cost followed by the battery storage and the wind turbine as shown in Table 10.5. For the converter system and PV module, O&M cost is quite small. Along with this techno-economic analysis, it is significant to analyse the monthly electrical contribution of the renewable and non-renewable module. The analysis result is shown in Fig. 10.13.

Figure 10.13 shows the monthly electrical energy generated by the renewable (i.e., the PV and the wind turbine systems) and the non-renewable (i.e., the diesel generator) devices. According to Fig. 17, it is observed that the wind module is contributing most significantly throughout the year with higher production during the months April to October. Though PV module contributes for the whole year, this contribution is quite smaller than that of the wind module. During the time of the monsoon, the PV unit produces a lesser amount of power but during this period wind energy is adequate to attain the required energy demand of the RO desalination unit. As this study area is located near the equator this location also experiences the winter rainfall during the months Nov to February. During this period power production from the wind module also decreases and the diesel generator has to contribute to the energy required during these months. Fig. 10.14 shows the yearly power share of the different energy sources.

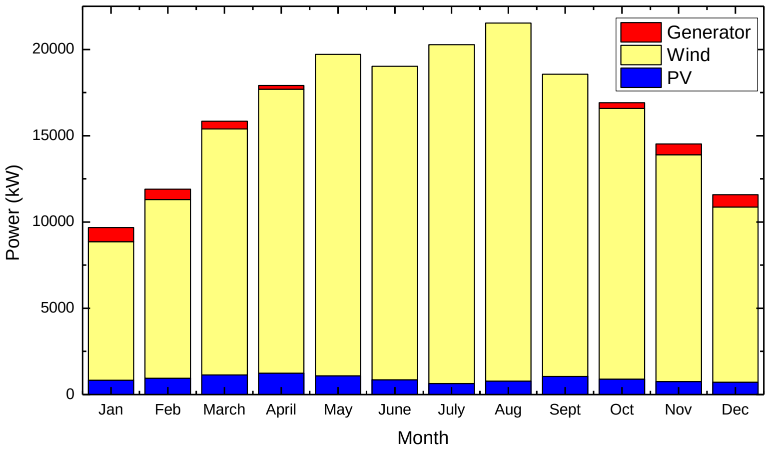


Fig. 10.13: Monthly average electric energy production scenario

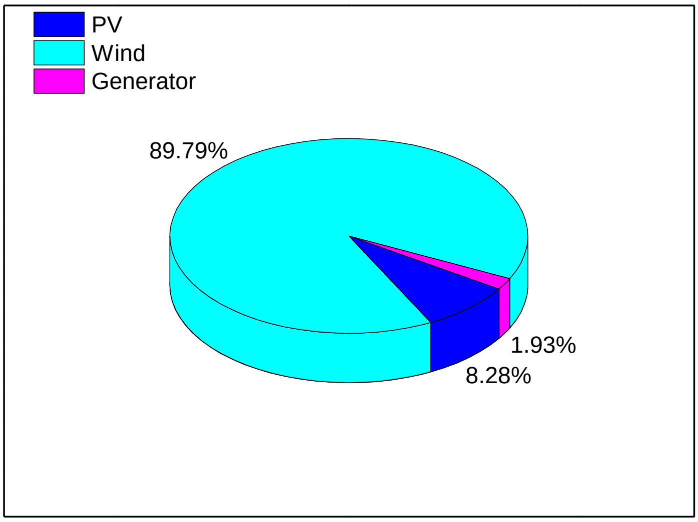


Fig. 10.14: Renewable and Non-renewable resources electricity sharing in percentage

According to Fig. 10.14, the wind module approximately provides above 90% of the required energy of the year. The contribution of the PV module is 8% of the yearly energy required and the rest is provided by the DG set. The study shows that 98% of the total energy required is supplied by two renewable resources whereas non-renewable resources supply only 2% of the total energy required. This is because the hours of operation of the DG set is kept low.

The project cash flow analysis is depicted in Fig.10.15. According to Fig. 10.15, each cost term share in NPC is illustrated. As this hybrid system consists of renewable devices, the major portion of this system cost is the capital cost followed by operation and maintenance (O&M) cost. The lifetimes of PV, wind, and generator are similar or more than project lifetime. So, the replacement cost is only applicable for the battery system and the converter. The fuel cost is associated only with the diesel generator. The salvage cost of this hybrid system is mostly recovered from the battery, the converter, and the diesel generator. Along with this techno-economic analysis, environmental impact assessment of this hybrid system is also important for this study.

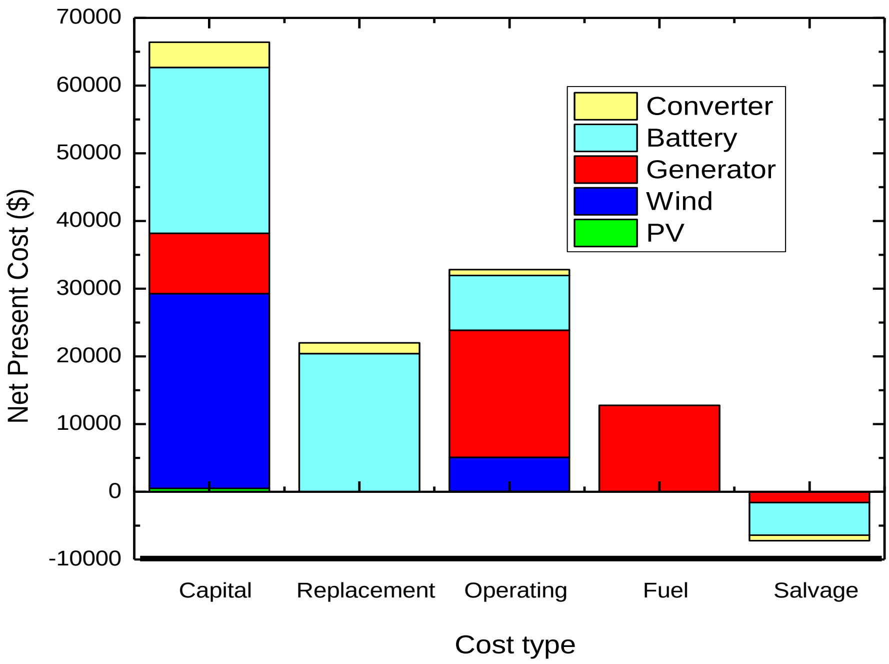


Fig. 10.15: Detail analysis of total system cost (NPC)

The GHG emission from the fossil-fuel based generator is harmful to humans, animals, and plants. It also affects the climate and contributes to global warming. The hybrid system proposed to supply power for the RO desalination unit suitable to the study area reduces this GHG emission to 2930 kg/year. The various concentrations of pollutants in the exhaust of the generator are summarized in Table 10.6. This GHG emissions is much lesser (approximately 90%) than only diesel generator-based power supply systems. The significant renewable energy integration leads to the reduction of GHG emissions and is able to make the system more environment-friendly.

Table 10.6: Emissions

Pollutant	Yearly quantity in Kg
CO_2	2,887
CO	18.2
UHC	0.794
PM	0.110
SO_2	7.07
NO_2	17.1

As the final step, the sensitivity analysis has been done to examine the reliability of the RO desalination unit combined with the hybrid energy system option.

10.4.4 Sensitivity analysis:

The sensitivity analysis is performed for a hybrid energy system by varying the price of renewable energy devices like the PV and the wind turbine. The capital cost of the PV varies within 0.5-1.5 times and the capital cost of the wind turbine varies within 0.5-2 times of the present cost. By varying both these capital costs, variations of the COE and the NPC are analysed in this sensitivity analysis. The changes of NPC with superimposing COE are shown in Fig. 10.16. Figure 10.16 shows that the system's COE and NPC mostly affected due to the variation of wind modules as compared to solar modules. According to the figure, variation of the PV capital cost does not have any impact on the NPC of the system. The COE of the system varies slightly when the capital cost of the PV module varies 0.5-1.1 times of the present cost. The COE of the system does not change above 1.1 times of the capital cost. On other hand, if the cost of the wind turbine increases 1.1 times of its present value there is not much increase in the COE of the system. If the increment is above this value, then there is significant change in the COE of the system and also it is similar for NPC. Hence, the analysis proves that the capital cost of the PV module has lesser impact on the system economy as compared to the capital cost of the wind turbine. So, the wind turbine cost variation will affect the economy of the system more. Hence this study indicates that the variation of the wind turbine module cost should be less to make this hybrid system economically less risky.

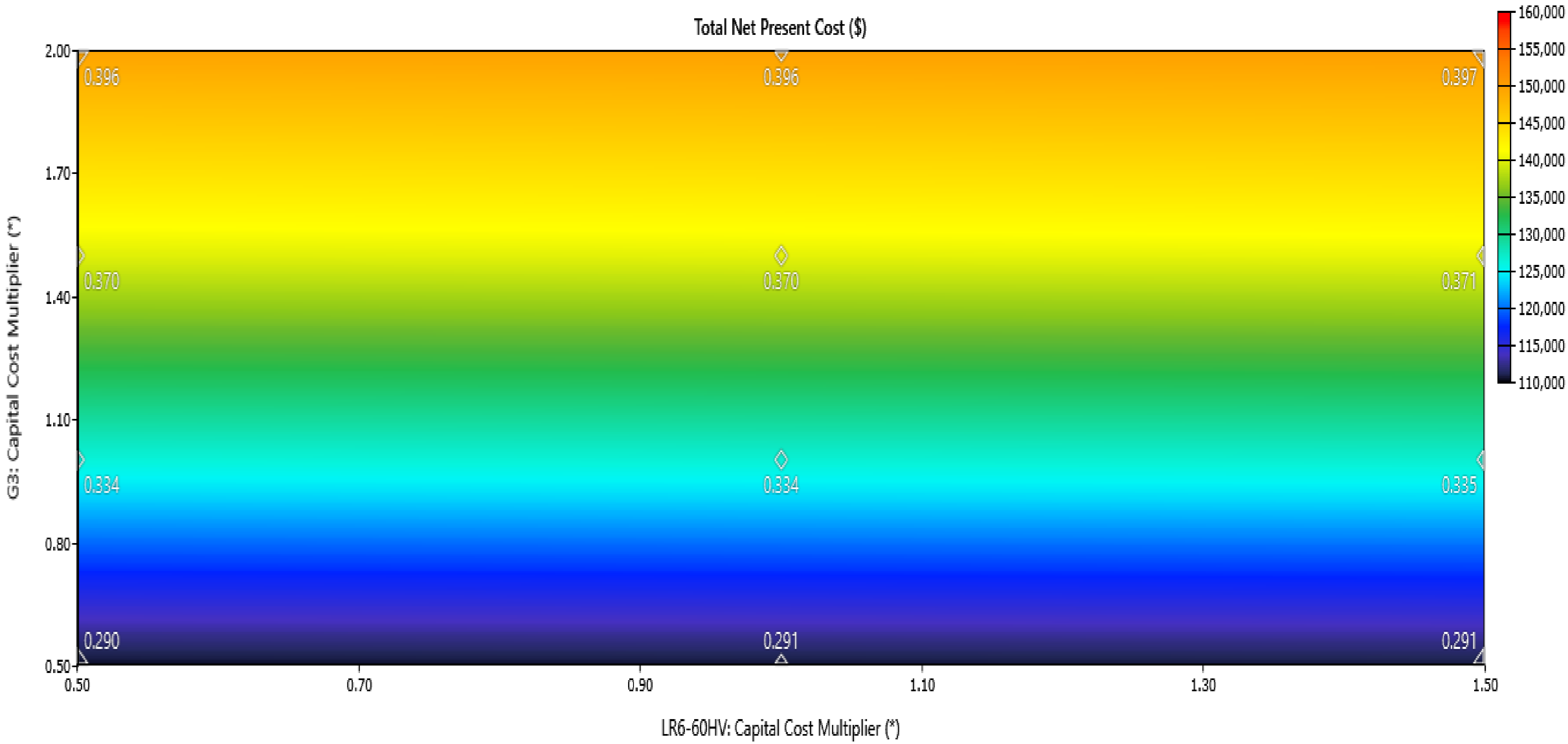


Fig. 10.16: NPC and COE variation with the component price variation

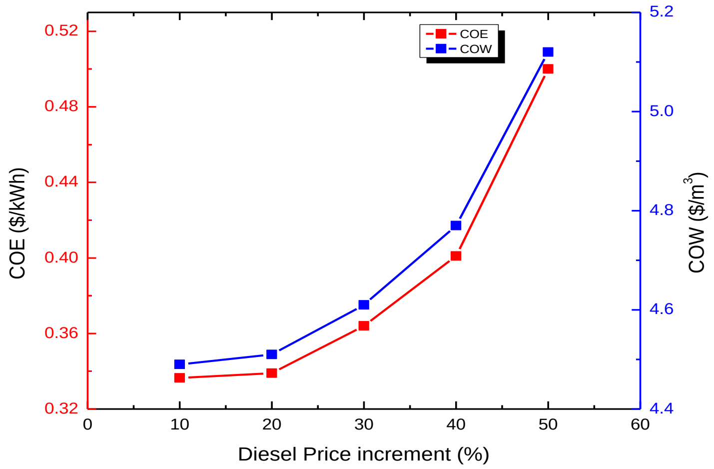


Fig. 10.17: Variation of COE and COW with Diesel price variation

Figure 10.17 shows how the percentage increment of the diesel price affects the COE and the COW simultaneously. If this price changes in the range of 5-50% then both the COE and the COW vary. In the range of 5-20% these values are less affected but after that both COE and COW increase sharply and the increment rate is very high. So, from this study, it is obvious that if the diesel price increases slightly, then only the system's COE and COW will become in a stable condition. If this increment is higher, then the system COE and COW will be affected significantly and the sustainability of the selected optimal combination will be greatly affected. Thus, from this partial sustainability assessment (including economy and environmental impact) it is concluded that the system sustainability will be severely affected by the variations of the wind turbine module and the diesel price due to higher system cost and also the significantly higher COW.

10.5 Summary of the chapter:

The study compared techno-economic aspects of different desalination units integrated with decentralized hybrid energy systems to obtain optimal solutions to supply potable water at least economic and environmental impact. The results of the analysis show that the RO desalination technique is the optimum sustainable solution to attain the demand of water at an optimum cost (COW). This study also concludes that the PV-wind-battery storage, supported by a DG system is the optimal energy combination to continuously supply energy to this desalination unit with the best economy and least environmental impacts. The cost of potable water produced from this desalination unit is \$4.57/m^3 with the CO_2 emission of 2887 kg/year. The COW and environmental impacts are reduced to 69% and 90% respectively by using this combination as compared to that of the fossil fuel-based other desalination techniques for the same water demand. By using lower capacity DG and restricted usage of the module minimizes the emission. The price of both the wind module and the diesel are needed to be low for the system to operate with the best economy.

Chapter-11

Conclusions and Future Work

11.1 Conclusions:

Global energy transition demands more renewable share in the energy mix. However, renewable energy has several limitations as a sole option for current global energy demand. Renewable resources are generally dilute, intermittent, vary widely with seasons and are not enough for meeting the demand solely. However, introduction of renewable power in the power mix is critical for energy transition towards better sustainability. Introducing renewable power in an optimal way depends on several factors and these factors are to be optimized for the best possible application of it. Priority of these factors to determine the most acceptable solution have some local constraints as well as global sustainability goals of economy, environment-friendliness and social acceptance. Also, these factors may have different priorities based on local or national constraints and mission plans.

India has currently high carbon intensive coal-based power generation. Also, it has limited access to electricity to the poor people at villages, specifically at remote locations. However, the Government of India is committed to Power for all Indian citizens. Extending grid power to several remote villages of India may be neither technically nor economically feasible. To achieve power access to the rural population of India including remote locations decentralized hybrid energy may be a suitable option. Suitable policy support at national and sub-national levels is also required to promote rural electrification. These policies need to be optimized for possible benefits against constraints. In this thesis, optimized hybrid renewable energy solutions using local resources have been explored for several rural areas including remote locations. Optimized solutions are explored to meet the sustainable development goals, specifically meeting economic, environmental and social criteria. To meet this objective several rural locations of India are explored for suitable hybrid distributed renewable energy options with uninterrupted, affordable power and possible minimum environmental impacts. Implementation of these new technologies need investment. Investors need to be assured for the risk assessment of return on investments (ROI). Uncertainty in ROI also has been explored for such distributed HRES using Monte Carlo Simulation. India also has large variations in topography. Energy demand at different rural locations of India widely varied due to these topographical variations. The need for energy services also varies in different geographical locations. Studies are conducted for seven different representative locations with different geographical and demographic characteristics to explore the solutions for varying conditions of India. Though power is the highest priority energy service for all these locations, some other energy services also have priority at specific locations. Having a long coast line and limited ground water availability, desalination is such a need for coastal villages of India. India has priority for the hydrogen economy as a national mission. Using excess renewable power generation to generate hydrogen, i.e., "green hydrogen", may be a big support for economic development of Indian villages using HRES. Storage is an integrated part of renewable energy supply due to intermittency and mismatch between demand and supply. Optimizing storage systems including selection of suitable dispatch strategies is inevitably an integrated part of this study. Generally, the optimum solution for any specific location does not converge for all sustainable development criteria to a single one. Hence, multi-criteria decision making is the option to decide the acceptable best sustainable solution for a specific location. Overall exploration for possible solutions of rural electrification of India by HRES at different locations of India has revealed several findings, some are common to different studied locations of India and rest are typically location specific.

Following are some of the observations for rural electrification irrespective of locations.

- The variation in power generation from different renewable energy resources, determines a mismatch between energy demand and supply. To minimize the demand and supply gap integration of small capacity storage modules with the decentralized HRES are inevitable.

- Sometimes only renewable-based energy systems supported by storage modules may not meet the demand during peak load. The capacity increment of the energy components may not be an economically feasible option, as it increases the cost of electricity of the system. This increased cost of electricity exceeds the cost of currently existing diesel-based limited power supply. Thus, irrespective of increasing the capacity of the energy components, integrating a small capacity diesel generator set may be a better option for a decentralized hybrid energy system, specifically for the Indian context.

- Assessment of different sustainability criteria, i.e., techno-economic optimization, environmental impact assessment and investment risk analysis generally did not converge to a single solution. A multi-criteria decision-making approach is finally used to decide an overall acceptable optimal solution.

However, there are certain observations which are according to the constraints of the selected location as:

- With the characteristics of local energy needs, the priority of energy strategies may vary for different locations of India.

- Determination of the most suitable location for developing decentralized hybrid energy systems may change due to several constraints and barriers.

- In line with the Indian priority of hydrogen mission, production of "green hydrogen" through excess electricity and using this hydrogen to produce electricity via fuel cell is found to be a suitable option specifically from techno-economic viewpoint.

- Developing desalination units integrated with a decentralized hybrid energy system depends on the local need of fresh water. Scarcity of fresh water and proximity to sea favors desalination integrated with renewable power.

11.2 Future scope of work:

- To improve techno-economic efficiency of the decentralized HESs the load and the weather forecasting may be augmented with the overall sustainability assessment.
- For an even better sustainable solution, social acceptance needs to be evaluated further for these emerged solutions.
- The obtained optimum decentralized HESs may further be developed into prototypes to check their performance for final commercial deployment.

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Appendices

Table A.1: Equations of the component

Sl. No.	Components	Working equations	Nomenclature	Reference
`1	PV module	$P_{PV}(t) = P_{PV,STC}.F_{PV}.\left(\frac{G_T}{G_{T,STC}}\right).[1 + \alpha_p(T_C(t) - T_{STC})]$ (i) $T_C\ (t) = T_a(t) + \left[\frac{NOCT-20}{800}\right] \times G_T$ (ii) $P_{PVT}(t) = N_{PV} \times P_{PV}(t)$ (iii)	P_{PV} (t): Output power of PV module at any time instant (kW); $P_{PV,STC}$: Rated power of the module in standard condition (kW); F_{PV}: Derating factor (%); G_T: Global solar irradiation incident on the module (kW/m^2); $G_{T, STC}$: Irradiation at standard condition (kW/m^2); α_p: Maximum power temperature coefficient (%/^{o}C); T_C: Cell temperature (^{o}C); T_{STC}: Temperature at standard condition (^{o}C); T_a: Ambient cell temperature at any time instant (^{o}C); NOCT: Normal operating cell temperature; P_{PVT}: Total solar power; N_{PV}: Number of solar modules	(Babatunde et al, 2022; Emad et al., 2021; mandal et al., 2018)
2	Wind module	$P_W = \begin{cases} 0 & V \geq V_{c-out}, V \leq V_{c-in} \\ \frac{P_r(V - V_{c-in})}{(V_{rw} - V_{c-in})} & V_{c-in} < V < V_{rw} \\ P_r & V_{rw} < V < V_{c-out} \end{cases}$ (i) $V_{hub-height} = V_{anem} \times \left(\frac{Z_{hub}}{Z_{anem}}\right)^{\gamma}$ (ii) $P_{WT}(t) = N_{WT} \times P$ (iii)	P_W: Output power of the module in kW; P_r: Rated power in kW; V: Wind speed at hub-height (m/s); V_{c-in} & V_{c-out}:cut-in and cut-out wind speed (m/s); $V_{hub-height}$: Wind speed at hub-height (m/s); V_{anem}: Wind speed at anemometer height (m/s); Z_{hub} & Z_{anem}: hub and anemometer height	(Emad et al., 2021)

			(m); γ: Hellman constant; P_{WT}: total wind power; N_{WT}: Number of wind turbine	
3	Hydro module	$P_{Hydro} = \frac{1}{2}.\rho_w.A.V^3.C_{p.H.}.\eta_{Hydro}$ (i)	P_{Hydro}: Hydro turbine output power (kW); ρ_w: Water density (kg/m^3); A: Hydro turbine area (m^2); V; Water flow (m/s); η_{Hydro}: Efficiency of hydro module (%); $C_{p, H}$: Performance coefficient	(Arevalo et al., 2020)
4	Storage module	$P_{batt,Cmax} = \frac{\min(P_{battery,cmax,kbm}, P_{battery,cmax,mcr}, P_{battery,cmax,mcc})}{\eta_{battery,C}}$ (i) $P_{battery,cmax,kbm} = \frac{kQ_1 e^{-k\Delta t} + Qkc\,(1 - e^{-k\Delta t})}{1 - e^{-k\Delta t} + c(k\Delta t - 1 + e^{-k\Delta t})}$ (ii) $P_{battery,cmax,mcr} = \frac{(1 - e^{-\alpha_c \Delta t})(Q_{max} - Q)}{\Delta t}$ (iii) $P_{battery,cmax,mcc} = \frac{N_{battery} \times I_{max} \times V_{nom}}{1000}$ (iv) $\eta_{battery,C} = \sqrt{\eta_{battery,rt}}$ (v)	Q_1: Available energy in storage at the beginning in kWh; Q: Total amount of energy in battery in the beginning (kWh); Q_{max}: Total capacity (kWh); c: Capacity ratio; k: Constant rate (1/h); α_c: Maximum charge rate (A/Ah); Δt: Time step length (h); $N_{battery}$; Number of batteries; I_{max}: Maximum charge current (A); V_{nom}: Nominal voltage (V); $\eta_{batter,c}$ & $\eta_{battery,rt}$: Battery charge efficiency and round trip efficiency	(Baneshi and Hadianfard, 2016)
5	DG module	$F = F_{0,DG} \times Y_{DG} + F_{1,DG} \times P_{DG}$ (i)	$F_{0, DG}$: Fuel curve intercept coefficient (Units/h/kW); Y_{DG}: Rated capacity (kW); $F_{1, DG}$: Fuel curve slope (Units/h/kW); P_{DG}: Electrical output (kW) F: Total fuel consumption	(Ramesh and Saini, 2020)
6	Converter module	$P_{converter} = \frac{P_{peak}}{\eta_{inverter}}$ (i)	$P_{converter}$: Converter size; P_{Peak}: maximum demand (kW);	(Emad et al., 2021)

				$\eta_{inverter}$: inverter efficiency	
7	Electrolyzer	$H = \eta . P$	(i)	H: Amount of hydrogen produced; η: efficiency of electrolyzer; P: Input electrical power	(Mehrjerdi et al., 2022)
8	Hydrogen tank	$H_1 = H_0 + H_c - H_d$	(i)	H_1, H_0, H_c, & H_d: Present hydrogen amount, previous hydrogen before, charge and discharge of hydrogen	(Mehrjerdi et al., 2022)
9	Fuel cell	$P_{FC} = N \times V_{FC} \times I_{FC}$	(i)	N: Total number of cells; I_{FC}: generated current (A); V_{FC}: Cell voltage (V)	(Mehrjerdi et al., 2022)

Table A.2: Parameters Equation

Sl. No.	Parameters	Working equations	Nomenclature	Reference
1	Technical i) Unmet Load (UL)	$UL = \frac{yearly\ non\ renewable\ load - served\ load}{yearly\ load}$ (i)	UL: Unmet load	(Ali et al. 2021)
	ii) Excess Electricity (EE)	$EE\ (\%) = \frac{E_{excess}}{E_{production}} \times 100$ (i)	EE: Excess electricity; E_{excess}: Annually produced excess electricity (kWh/y); $E_{production}$: Total produced electricity (kWh/y)	(Nag & Sarkar, 2018)
2	Economic i) Annualized cost (C_A)	$C_A = C_{IC} + C_{RC} + C_{O\&M} + C_{DG}$ (i)	C_A: Annualized cost; C_{IC}, C_{RC}, $C_{O\&M}$, C_{DG}: Initial, replacement, operation and maintenance and fuel cost	(Khan et al., 2021)
	ii) Cost of electricity (COE)	$COE = \frac{C_A}{E_t}$ (i)	E_t; Annualized electricity consumption	
	iii) Net Present cost (NPC)	$C_{NPC} = \frac{C_A}{CRF\ (i,t)}$ (i)	CRF: Capital recovery factor; i:	

			$CRF\ (i,t) = \frac{i\ (1+i)^k}{(1+i)^k - 1}$ (ii) $i = \frac{i_n - f}{1+f}$ (iii)	yearly interest (%), t: project lifetime (y); i_n: nominal interest (%); f: inflation rate	
	iv)	Operation & Maintenance cost ($C_{O\&M}$)	$C_{om,other} = C_{om,fixed} + C_{cs} + C_{emission}$ (i)	$C_{om,\ fixed}$: Fixed operation and maintenance cost; C_{CS} & $C_{emission}$: Capacity shortage and emission penalty cost	(Nag &Sarkar, 2018)
	v)	Penalty Cost	$C_{cs} = c_{cs} \times E_{cs}$ (i) $C_{emission} = \frac{c_{CO2}.M_{CO2}+c_{CO}.M_{CO}+c_{UHC}.M_{UHC} + c_{PM}.M_{PM}+ c_{so2}.M_{so2}+c_{NO2}.M_{NO2}}{1000}$ (ii)	C_{cs}: penalty for capacity shortage; E_{cs}; total yearly capacity shortage (kWh/y)	(HOMER ® 2017)
	vi)	Cost of water (COW)	$COW = \frac{C_d \times CRF + C_{tank} \times CRF + C_{o\&m} + C_{elect} \times E_{fromhs}}{Q_{annual}}$ (i)	C_d: overall desalination system cost; C_{tank}: water reservoir cost (\$); $C_{o\&}$m: overall operational and maintenance price (\$); C_{elect}: price of generated electricity generated (\$/kWh); E_{fromhs}: price of electricity from sources (kWh); Q_{annual}: yearly produced water (m^3/y)	(Gokcek & Gokcek, 2016)
3	Environmental i)	Renewable fraction (RF)	$RF = 1 - \frac{E_{nr}+H_{nr}}{E_S+H_S}$ (i)	E_{nonren}: non-renewable electric production (kWh/y); H_{nonren}: non-renewable thermal production (kWh/y); E_{served}: total electric load served; H_{served}: total thermal	(HOMER ®, 2019)

				utility delivered	
ii)	Loss of Power Supply Probability (LPSP)	$LPSP = \frac{\sum_{i=1}^{n} E_{deficit}}{\sum_{i=1}^{N} P_{load}}$	(i)	$E_{deficit}$: energy deficit per year (kWh); P_{load}: required cumulative electrical energy (y).	(Ray et al., 2018)

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