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Research paper

Sustainability evaluation of power generation technologies using Multi-Criteria Decision Making: The Kenyan case

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ABSTRACT

Kenya expects a high growth in energy demand due to its high demographic and economic growth as well as increasing industrialization. In that regard, the government of Kenya has already shown interest to expand its power supply which includes coal-fired power plants. However, many previous studies conducted to evaluate the Kenyan energy planning scenarios were limited to technical aspect such as dynamic power consumption and demand forecasting; techno-environmental aspect such as low carbon capacity expansion; techno-economic electricity expansion aspect and economic, techno-environmental electricity expansion aspect. The concern of evaluating all the potential Kenyan power options against sustainability dimensions as a whole was not addressed since selecting power technology options has become a multidimensional problem. Therefore, this study aimed at prioritizing Kenyan power technology options using sustainable dimensions: Economic, Social, Environmental and Technical. This research applied Multi-criteria decision making (MCDM) method which is an interesting tool able to bring together several variables to handle a decision making problem. Hence, energy options were evaluated against the four sustainable dimensions (Economic, Social, Environmental and Technical) combining 17 energy indicators and a hybrid AHP–TOPSIS technique was used for that purpose. Results showed that Solar PV and Wind are the most promising technologies in Kenya. Although CSP has not been privileged by Kenyan policymakers, it ranks among the first-three promising technologies, except for economic scenario raking this option the last. Five different analyzed scenarios (Economic privileged, Technical privileged, Environmental privileged, Social privileged, Equal importance) showed the robustness of Solar PV in the all sustainable dimensions. This study has provided a critical policy contribution to the Kenyan government and energy projects investors by solving the dilemma of technologies prioritization in capacity expansion.

1. Introduction

The Sub-Saharan Africa (SSA) is greatly characterized by poor energy access. Around 80% of SSA population considerably rely on traditional biomass as cooking fuels mainly charcoal, animal dung or agricultural residues (Dagnachew et al., 2019; Johnson et al., 2017). Furthermore, it is expected that more than 640 million people in Africa will still rely on biomass fuels for cooking by 2040 (Carvalho et al., 2019). In East African Community (EAC), Kenya has made a significant progress in terms of modern energy access (Manirambona et al., 2022). According to The World Bank data, access to electricity in Kenya was 69.7% in 2019, the highest in EAC. In addition, Kenya has made a significant progress in planning for its energy sector compared to other East African countries (Manirambona et al., 2022). However, like other SSA countries, Kenya is not an exception, the use of firewood or charcoal as fuel is the main driver for the overall households' consumption. The use of biomass represents 68% in overall Kenyan energy mix while electricity is only represented by 9% (Takase et al., 2021).

Despite the good progress in terms of energy access (Moner-Girona et al., 2019), it is obvious that Kenyan energy demand will keep growing for decades due to high growth of country's population (NCPD and UNFPA, 2020), national economy (The World Bank Group, 2021) as well as expected ongoing industrialization activities (Ministry of Industrialization and Enterprise Development, 2015). Hence, all these make the country to face with power supply expansion needs as even the current national electricity supply is not sufficient to meet the demand (Takase et al., 2021). However, this country is endowed with huge energy resources made of renewable energy (RE) resources and fossil fuels reserves (Hafner et al., 2019). The country is gifted with 6 GW of hydropower potential; estimated 10 GW of geothermal potential; good insolation favorable for solar photovoltaic (PV) and Concentrating Solar Power (CSP); Biomass and Wind resources;

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Table 1
Overview of Kenyan energy sector and energy resources potentials.
Source: (Hafner et al., 2019; Ministry of Energy, 2018; Musonye et al., 2021; The Kenya Power and Lighting Company, 2019).

Electricity Access (2019)[a]	Country's installed Capacity (Imports excluded) (MW)			Energy Resources potential/reserves						
	Tot. (year)	Share		Hydro (GW)	Geothermal (GW)	Solar (kWh/m^2/d)	Wind (m/s)	Biomass (PJ)	Coal (million tons)	Oil (10^6 barrels)
69.7%	2741 (2019)	Hydro	833.797	6	10	4 – 6	> 6	260	400	766
		Geother.	684							
		Wind	336.55							
		Biomass	26							
		Solar	50.94							
		Thermal	810.52							

[a] The World Bank data (2019): Access to electricity (% of population).

and huge untapped reserves of Oil and Coal (Hafner et al., 2019; Ministry of Energy, 2018; Musonye et al., 2021; The Kenya Power and Lighting Company, 2019). Table 1 summarizes the Kenyan energy sector.

Kenya has structured its energy policy in a way that favors high penetration of RE in order to meet its energy demand while reducing greenhouse gas emissions (Oluoch et al., 2021). Although the country's energy policy has recently endeavored to increase RE share in order to face the growing energy demand (Fobi et al., 2018; Moner-Girona et al., 2019), its focus on techno-economic aspects may lead to non-sustainability. The public involvement is neglected in most developing countries when planning new energy projects (Oluoch et al., 2020). For instance, local population of Marsabit County in Kenya was found exposed to new conflicts caused by land and employment issues after a wind park of 310 MW was built in their region (Hardt, 2018).

Apart from RE sources projects, the Kenyan government has already showed interest in building coal-fired power plants, a first 960 MW coal-fired power plant is expected to be commissioned in 2024 (Ministry of Energy, 2018). Hence, a sustainable power generation is a necessity. It is crucial to choose power options considering their future sustainability. This requires to make a trade-off between "power generation and protection of environment, reliability and sustainability, social and economic welfare" (Kuo and Pan, 2018).

According to Kosenius and Ollikainen (2013), social, economic and environment aspects are critical aspects when selecting an optimal power option.

Over the years, many researchers have relied on Multi-criteria Decision Method (MCDM) to propose sustainable option in energy sector using different techniques applied in MCDM. The PROMETHEE "Preference Ranking Organization METHod for Enrichment Evaluations" and AHP "Analytical Hierarchy Process" were used to assess power generation technologies for German municipal area (Oberschmidt et al., 2010) and for Niger country (Bhandari et al., 2021), respectively. The Tunisian electricity system transformation strategies were assessed using TOPSIS "Technique for Order Preference by Similarity to Ideal Solutions" (Brand and Missaoui, 2014). VIKOR "VIsekriterijumsko KOmpromisno Rangiranje" method helped to select a best solution for rural electrification of Venezuelan remote rural locations (Rojas-Zerpa and Yusta, 2015) whereas ELECTRE "Elimination and Choice Translating Reality" was depended on to evaluate action plan for diffusion of RE technologies at regional scale in Sardinia (Beccali et al., 2003).

Many other techniques applying MCDM exist and each method has its strengths and weaknesses (Kiplagat et al., 2011; Kumar et al., 2017; Oberschmidt et al., 2010; Özcan and Çelebi, 2011; Wang et al., 2009). However, all these methods use same steps for their application (Fülöp, 0000):

i. *Define the problem;*
ii. *Determine requirements;*
iii. *Establish goals;*
iv. *Identify alternatives;*
v. *Define criteria;*
vi. *Select a decision making tool;*
vii. *Evaluate alternatives against criteria;*
viii. *Validate solutions against problem statement.*

Hence, the large variety of techniques applied in MCDM make it challenging when selecting a technique to be used for a particular case study. From the review of Stojanovic (2013), AHP was found among the most used method in MCDM. According to the analysis of Kurka and Blackwood (2013), AHP came out as the best method before DELTA and PROMETHEE II. Similarly, the review of Pohekar and Ramachandran (2004) ranked AHP in the first position before PROMOTHEE and ELECTRE among most used tools in sustainable energy planning. However, many researchers opted to use more than one methods in their studies (da Ponte et al., 2021; Guleria and Bajaj, 2020; Kizielewicz and Szyjewski, 2020; Luo et al., 2020; Mojaver et al., 2020; Sindhu et al., 2017; Zola et al., 2019) and this enables to draw essential conclusions (Kumar et al., 2020). The AHP method is the most preferred for combination with others (Løken, 2005).

Many previous energy sustainability assessment studies were carried out in different countries to facilitate energy decision making (e.g.: Ali Sadat et al., 2021; Amer and Daim, 2011; Ayik et al., 2020; Azerefegn et al., 2019; da Ponte et al., 2021; Elkadeem et al., 2021; Evans et al., 2009; Guleria and Bajaj, 2020; Haddah et al., 2017; Luo et al., 2020; Simsek et al., 2018; Strantzali et al., 2017; Strantzali and Aravossis, 2016; Troldborg et al., 2014; Tsoutsos et al., 2009; Vlachokostas et al., 2021; Zola et al., 2019). While fossil fuels based power plants are still considered as power options to be implemented in many countries (Kenya included), many of the previous energy sustainability assessment studies did not consider all possible energy resources in the evaluation; most of them concentrated on assessing RE for energy generation (Amer and Daim, 2011; Ayik et al., 2020; Evans et al., 2009; Haddah et al., 2017; Strantzali and Aravossis, 2016; Troldborg et al., 2014; Tsoutsos et al., 2009), specific technologies options (Ali Sadat et al., 2021; Bhandari et al., 2021; da Ponte et al., 2021; Simsek et al., 2018; Strantzali et al., 2017; Vlachokostas et al., 2021; Zola et al., 2019) and RE site selection (Elkadeem et al., 2021; Guleria and Bajaj, 2020; Luo et al., 2020).

Although fossil fuels are the main sources of pollution and greenhouse gas emissions, they still present some advantages such as being the cheapest option for electricity generation in many countries. Nevertheless, these sources are challenged by their limited resource potentials in future and are expected to be depleted. On the other hand, RE technologies being the key to green and secure energy in the future, they still have some obstacles such as the low ability to respond to peak-load and some technologies are still very expensive to be exploited. Therefore, due to these barriers/opportunities in exploiting energy resources, this study sought to consider the diversification of all available energy resources in view of sustainability with Kenya as a case study.

Many previous studies were conducted in Kenya to evaluate Kenyan energy planning scenarios. However, most of them have analyzed the technical aspect such as dynamic power consumption (Fobi et al., 2018) and demand forecasting (Lahmeyer International, 2016; Mbae and Nwulu, 2020; Otieno et al., 2018), the techno-environmental aspect such as low carbon capacity expansion (Carvallo et al., 2017; Kehbila et al., 2021), the techno-economic electricity expansion aspect (Moksnes et al., 2020; Moner-Girona et al., 2019) and economic, techno-environmental electricity expansion aspect (Musonye et al., 2021).

Furthermore, previous studies have also analyzed the Kenyan power system using varied methods. Kenya's electrification strategies were investigated targeting the year 2030 (Moksnes et al., 2020). The investigation relied on a combination of the tools OnSSET/OSeMOSYS "Open Source Spatial Electrification Tool/ Open Source energy MOdelling SYStem" and fossil fuels, mainly coal and natural gas, were found much important for the optimum Kenyan energy mix system. Musonye et al. evaluated greenhouse gas emissions reduction of the Kenyan energy system using TIMES "The Integrated MARKAL/EFOM System" (Musonye et al., 2021). By using SWITH "Solar and Wind energy Integrated with Transmission and Conventional sources", the Kenyan power system was analyzed in different paths under diverse scenarios (Carvallo et al., 2017). Lahmeyer International used a combination of LIPS–OP/XP "Lahmeyer International Power System-Operation Planning/ Expansion Planning" to explore suitable pathways to expand the Kenyan power system from 2015 to 2020 (Lahmeyer International, 2016). By using LEAP "Long-range Energy Alternatives Planning", different pathways of decarbonization strategies of the Kenyan power system were analyzed for the period 2010–2040 (Kehbila et al., 2021). However, to the authors' knowledge, no previous study has addressed the concern of evaluating all the potential Kenyan power options against sustainability dimensions as a whole since selecting power technology options has become a multidimensional problem (Strantzali et al., 2017). The MCDM method has not been applied in this context for the Kenyan case. Consequently, there is a need to conduct an analysis considering different assessment criteria. The application of MCDM method is an interesting tool able to bring together several variables in order to handle a decision making problem. The research question of this study is: How sustainable are the potential power technology alternatives to be implemented in Kenya? To answer this question, different power generation technology options were appraised based on the country's potential energy resources. These technologies were assessed based on several sustainable indicators grouped in four sustainable dimensions: Economic, Social, Environment and Technical.

After weights of different indicators are determined by the application of the AHP, the TOPSIS model was used to rank different power options due to its ability to work with fundamental ranking and its full use of allocated information (Kumar et al., 2017). Nevertheless, TOPSIS method is disadvantaged by failing to consider experts (Luo et al., 2020) and hence, a hybrid TOPSIS-AHP method was used in that regard.

The scope of this study is limited to power generation supplied by local power plants, the influence of imports and exports are not considered. Additionally, it was assumed that no more reserves of fossil fuels will be discovered in future.

This study sought to contribute to the Kenyan energy policy with a sustainability perspective for their future power system and this work can be adapted to other countries with similar gaps, for instance the EAC countries (Manirambona et al., 2022), by involving a country's energy experts and stakeholders for overall assessment of input indicators. This would provide additional information to the Kenyan policy-makers as well as interested stakeholders on a best option with a sustainability aspect.

This article is organized as follows: the introduction part of the study is detailed in Section 1 while the methodology showing the application of the hybrid AHP–TOPSIS is presented in Section 2. Results of the study are presented and discussed in Section 3. The Section 4 gives conclusions and recommendations.

2. Methodology

This section describes the methodology used to evaluate the power generation technologies in Kenya. Data used are also described. The problem and decision making tool being defined in introduction section, the other steps of MCDM are presented in this methodology section.

2.1. Selection of power generation alternatives

This study built its selection on the energy resources potential in Kenya as well as on government willing to integrate them in their future power generation.

Therefore, Kenya presents eight technologies which are Hydropower, Geothermal power, Biomass power, Wind power, Solar PV, Concentrated Solar Power (CSP), Coal and Oil-fired power plants. The coal-fueled power plant is not a technology under operation as of 2022 in Kenya, but it was included in the different alternatives for the reason that the Kenyan government has already showed interest in this project. For instance, the first coal-fired power plant project of 960 MW using imported coal is expected to be operational in 2024 (Ministry of Energy, 2018).

2.2. Establishment of criteria and sub-criteria

For the purpose of sustainable development, the IAEA worked together with IEA and other international organizations to provide a set of 30 energy indicators focusing on social, environmental and economic dimensions (IAEA, 2005). However, many researches have been relying on opinion of country's experts for analysis and validation of the indicators to be used depending on energy project type. For instance, Brand and Missaoui (2014) used 13 indicators validated by experts in their country when assessing different scenarios for Tunisian electricity mix. In the same way, future scenarios of Portuguese power generation was evaluated using 13 indicators after experts consultation (Ribeiro et al., 2013). In analyzing sustainability of future electrification options of a Greek Island, Strantzali et al. (2017) opted for 7 indicators. A rural electrification project was planned with the help of MCDM using 13 indicators for sustainable option selection (Rojas-Zerpa and Yusta, 2015).

Therefore, in order to harness available energy resources in sustainable way, energy experts in Kenya were involved. A list of 20 indicators were selected and analyzed in accordance to literature review on most used for energy alternatives assessment (Brand and Missaoui, 2014; Liu, 2014; Ribeiro et al., 2013; Shaaban et al., 2018; Strantzali et al., 2017). This list was presented to the experts for validation. Hence, 17 indicators (often named sub-criteria in this study) were agreed and used for this study. The selection made here included some of the eight major indicators "efficiency, installed capacity, investment cost, O&M cost, CO_2 emissions, land use, job creation and social acceptability" highlighted in the review of Strantzali and Aravossis (2016) for energy planning projects.

Although SDI are grouped into three dimensions, Social, Economic and Environment (Vera and Langlois, 2007), many researchers used additional dimensions based on their study context. However, most all sustainable indicators for assessing power

Table 2
Criteria and Sub-criteria determination.

Criteria	Sub-criteria	Code	Unit	Benefit attribute
Economic: C_1	Capital cost	C_{11}	USD/kW	−
	Fix. O&M cost	C_{12}	USD/kW-yr	−
	Var. O&M cost	C_{13}	USD/MWh	−
Technical: C_2	Reliability	C_{21}	–	+
	Capacity factor	C_{22}	%	+
	Technology maturity	C_{23}	–	+
	Resource availability	C_{24}	TWh/year	+
	Ability to respond to peak load	C_{25}	–	+
Environmental: C_3	Land requirement	C_{31}	m^2/kW	−
	CO_2 emissions	C_{32}	g/kWh	−
	NOx emissions	C_{33}	g/kWh	−
	SO_2 emissions	C_{34}	g/kWh	−
	CH_4 emissions	C_{35}	g/GJ	−
	Water consumption	C_{36}	kg/kWh	−
Social: C_4	Job creation	C_{41}	Total job-years/GWh	+
	Safety risks	C_{42}	Fatalities/GWeyr	−
	Social acceptability	C_{43}	%	+

technologies can be classified into four groups "criteria" (Strantzali and Aravossis, 2016). Therefore, four criteria were used in the evaluation in this present study: economic, technical, environmental and social. The technical dimension was added as it was found to have a growing consideration in recent researches on energy sustainability (Amer and Daim, 2011; Liu, 2014; Rojas-Zerpa and Yusta, 2015; Shaaban et al., 2018; Strantzali et al., 2017; Strantzali and Aravossis, 2016).

Hence, 17 sub-criteria were used to evaluate the different technologies. Table 2 shows the criteria with their associated sub-criteria selected. The sustainability targets are indicated by "+" (i.e. more is better) and by "−" (i.e. less is better).

2.3. Indicators analysis: Sub-criteria evaluation

The data for the indicators used were taken from published reports by international organizations (i.e. IRENA), local publications (i.e. Ministry of Energy) and other similar previous conducted studies in other countries. The data were presented to the countries' energy experts for validation in the context of local situation. Crystalline solar PV modules for PV plants (utility scale), Solar thermal tower with storage, Gas combined cycle (new built) and coal (new built), Diesel reciprocating engine generators for oil-fired power plants and Onshore wind were assumed in this study.

2.3.1. Technical indicators

2.3.1.1. Reliability. The reliability implies the probability for a system to perform appropriately for a precise time duration without any repair during operation (Z. Biserčić and S. Bugarić, 2021). This indicator is often considered as qualitative parameter (Beccali et al., 2003). Its evaluation was based on data obtained from (Bhandari et al., 2021; Troldborg et al., 2014). The different technologies and their reliability values are highlighted in Table 3.

2.3.1.2. Capacity factor. This parameter, expressed in %, was obtained from IRENA (2015) for hydropower; IRENA (2012) and Lazard (2017) for Biomass and Oil; Lazard (2020) for PV, CSP, Wind, Geothermal and Coal power plants. The values of capacity factor of the technologies under investigation are shown in Table 3.

2.3.1.3. Technology maturity. This indicator is very important in the planning process. It is a qualitative indicator and reveals a state-of-art of a given energy technology. Hence, scale points from "1" (low technology maturity, i.e. only laboratory tested) to "5" (highest technology maturity, i.e. commercially available with high market penetration) were used for its assessment. The scale points were considered based on literature review on various previous studies (e.g.: Beccali et al., 2003; Troldborg et al., 2014; Tsoutsos et al., 2009) where this indicator was addressed. Data for technology maturity were considered based on the research of Troldborg et al. (2014), Held et al. (2017) and Alabbasi et al. (2022). According to Alabbasi et al. Wind is high mature technology, PV a mature and CSP a least mature technology (Alabbasi et al., 2022). Additionally, the study of Doukas et al. (2007) revealed that Coal is a less mature technology than Biomass while Natural Gas is the highest. Table 3 includes the technology maturity for different technologies.

2.3.1.4. Resource availability. This is a key parameter in this study. The different alternatives were chosen based on energy resources potential in the country. The data in TWh–yr for Hydro, PV, CSP and Wind were obtained from Hafner et al. (2019). It should be noted that these data represent techno-economical feasible energy potential. Some data were not found in TWh/year and conversion was done by assuming the reserves for coal and oil will be used up to 2040 and no additional reserves will be found in future. The estimated 10 GW (Hafner et al., 2019; Ministry of Energy, 2018) of geothermal potential was converted in TWh–yr; the 260 PJ biomass potential (Hafner et al., 2019) were converted in TWh–yr; the estimated 0.77 billion barrels of oil reserves (Hafner et al., 2019) were converted in TWh–yr (1 million barrels of oil equivalent = 1.7 TWh); the estimated discovered 400 million tons of coal reserves (Ministry of Energy, 2018) were converted in TWh–yr (1 million tons of coal equivalent = 8.4 TWh).

The energy resources potentials expressed in TWh/year are presented in Table 3.

2.3.1.5. Ability to respond to peak load. This is a qualitative indicator. The ability to respond to peak load is high for Natural Gas and Oil fired power plants. For base-load power plants (e.g.: Coal and Nuclear) their ability is low compared to the previous power plants and higher than intermittent RE (e.g.: PV, Wind). Therefore, this indicator was evaluated points between "−2" (low ability)" and "+2" (high ability) based on data suggested in Brand and Missaoui (2014). Hydropower was considered to be of high ability due to its fast startup time and hydropower plants with reservoir was assumed. Values for this indicator are presented in Table 3.

Table 3
Technical indicators.

Alternative	Reliability Qual. [1, 5]	Capacity factor (%)	Technology maturity Qual. [1, 5]	Resource availability (TWh/year)	Ability to respond to peak load Qual. [−2, +2]
Hydro	4	25–80	5	25	+2
PV	2	21–34	4	23000	−1
CSP	2	39–68	3	15400	+1
Wind	4	38–55	5	1800	−1
Geothermal	5	80–90	4	87.6	+1
Biomass	4	80–85	4	3.61	0
Oil	4	10–95	5	65.09	+2
Coal	4	63–83	3	162.82	0

2.3.2. Economic indicators

2.3.2.1. Capital cost. Access to investments is one of the barriers for energy projects implementation in African countries (Muzenda, 2009). Therefore, the capital cost needed to construct 1 kW for the different power technologies was used in this evaluation. Lazard analysis for total capital cost (USD/kW) for PV, CSP, Wind, Geothermal and Coal power plants (Lazard, 2020) was used. The data for hydropower were obtained from IRENA (2015) while data for Biomass and Oil were found in Lazard (2017). These data are presented in Table 4.

2.3.2.2. O&M (operation and maintenance) cost. The fixed O&M (USD/kW-yr) and variable O&M (USD/MWh) costs were considered in this study. Data were obtained from the analysis of Lazard for PV, CSP, Wind, Geothermal and Coal (Lazard, 2020); for hydropower in IRENA (2015) and Biomass in Lazard (2017). The different data are shown in Table 4.

2.3.3. Environmental indicators

2.3.3.1. Land requirement. The land requirement for power plants is always a big concern. In this study, the data suggested by Chatzimouratidis and Pilavachi (2008) were used for Hydro, PV, Wind, Geothermal, Biomass, Oil, Coal. Data for CSP was obtained from Troldborg et al. (2014). Data for land requirement for the different technologies are shown in Table 5.

2.3.3.2. CO_2, NO_X, SO_2 and CH_4 emissions. When the resources are used for power generation, they are subject to pollution. The life-cycle emission from these alternative technologies was obtained from Kuo and Pan (2018) and Steen (2001) for Coal, Oil, Biomass, Wind and Hydropower; from Chatzimouratidis and Pilavachi (2008) for PV and Geothermal; and from Peter Viebahn, Stefan Kronshage, Franz Trieb (DLR), Y. L. (CIEMAT) (2008) for CSP. The emissions data from the different technologies are shown in Table 5.

2.3.3.3. Water consumption. Water is consumed during different phases of lifecycle of a power plant and water demand by energy sector is an emerging problem (Colmenar-Santos et al., 2014; Onat and Bayar, 2010). Hence, it is an important parameter in this case study since Kenya is known to be a dry country and is among countries with significant water stress (Marshall, 2011). The water consumed during operation of power plants was the main focus in this study. This mainly refers to the quantity of water consumed in cooling systems (e.g.: Fossil fuels, Nuclear, CSP, Geothermal and Biomass power plants), cleaning process (e.g.: Solar PV and CSP) and water losses by evaporation (e.g.: Hydropower). Different values were obtained from Evans et al. (2009) and Onat and Bayar (2010) for PV, Wind, Hydropower, Geothermal and Coal; from Colmenar-Santos et al. (2014) for CSP; and Rovere et al. (2010) for Biomass (based on Bagasse). The water consumption in operation of wind power plants is almost 0 kg/kWh (Rovere et al., 2010) while solar PV consumes little amount (less than 1 kg/kWh) (Onat and Bayar, 2010) in cleaning process. Data for water consumption for the different technologies are shown in Table 5.

2.3.4. Social indicators

2.3.4.1. Job creation. The job creation refers to lifetime of the technologies which include manufacturing, construction, installation and O&M/fuel processing. Data for the different technologies were obtained from Bacon and Kojima (2011) and Wei et al. (2010) based on direct generated jobs/GWh. Oil and gas are supposed to have a same employment factor (Rutovitz et al., 2015). The data for these indicators for the different technologies are presented in Table 6.

2.3.4.2. Safety risks. Risk indicator is an important factor that contributes to decision making when formulating energy policies. These parameters expressed in form of fatality rate (Fatalities/ GW_eyr) were taken from Burgherr et al. (2011) for the different technologies. No data was found for CSP technologies from literature review. Hence, fatalities caused by lifecycle of solar PV power plants were assumed for CSP. The data for fatalities caused by the different technologies are shown in Table 6.

2.3.4.3. Social acceptability. This parameter is a qualitative indicator which is assessed through consultation with local community for their views. Some previous studies used qualitative scale for social acceptance evaluation (Brand and Missaoui, 2014; Troldborg et al., 2014). For the case of this study, results (in percentage) from a nationwide survey conducted by Oluoch et al. (2020) in Kenya was used. Values for public positive attitudes towards different energy technologies from that survey's feedback were used in this study (see Table 6).

2.4. Ranking different power supply options

This study evaluated all the power technology options in the country by using MCDM approach. Four criteria were considered: technical, social, economic and environmental. A hybrid AHP/TOPSIS was used to rank different alternative power technologies, targeting the roadmap 2040.

2.4.1. Weights of criteria and sub-criteria

The AHP method was used to determine the weights for the criteria considered. The weights of criteria and sub-criteria were evaluated in a pair-wise comparison using scoring scale of Saaty (1987) as shown in Table 7. Their importance were regarded to power technologies selection according to feedback from participants (energy experts at country level) in questionnaire that was designed. Hence, a survey was used for this purpose.

Regarding the minimum or maximum number of experts to be involved when collecting these data and views, different studies used various number of participants to accomplish their research results. By using Fuzzy AHP method, Ali Sadat et al. (2021) relied on ninety-one respondents. Elkadeem et al. (2021) depended on seven energy experts for pairwise comparison of sustainability indicators while Al Garni et al. (2016) relied on twenty experts' opinions in their survey regarding the MCDM process.

Therefore, 40 respondents were involved in this survey. These respondents were energy specialists (researcher in energy studies

Table 4
Economic indicators.

Alternative	Capital cost (USD/kW)	Fixed O&M cost (USD/kW-yr)	Var. O&M cost (USD/MWh)
Hydro	450–3500	20–60	2.00
PV	825–975	9.50–13.50	–
CSP	6000–9090	75.00–80.00	–
Wind	1050–1450	27.00–39.50	–
Geothermal	4500–6050	13.00–14.00	9.00–24.00
Biomass	1700–4000	50.00	10.00
NG	700–1250	14.50–18.50	2.75–5.00
Oil	500–800	10.00	10.00

Table 5
Environmental indicators.

Alternative	Land requirement (m^2/kW)	CO_2 (g/kWh)	NO_X (g/kWh)	SO_2 (g/kWh)	CH_4 (g/GJ)	Water consumption (kg/kWh)
Hydro	750	2–20	0.004–0.06	0.001–0.03	–	65–70
PV	35	49.174	0.178	0.257	–	1
CSP	40	13 –19	0.054 – 0.082	0.035 – 0.049	–	3.02
Wind	100	3 – 41	0.02–0.11	0.02–0.09	–	0
Geothermal	18	18.913	0.28	0.02	–	12–300
Biomass	5000	8.5–130	0.08–1.7	0.03–0.94	40	18.5–250
Oil	2.5	530 – 900	0.5–1.5	0.85–8	8	78
Coal	2.5	660 –1050	0.3–3.9	0.03–6.7	5.5	78

Table 6
Social indicators.

Alternative	Job creation (Total job-years/GWh)	Safety risks Fatalities/GWeyr)	Social acceptability (%)
Hydro	0.27	0.945	68
PV	0.87	0.000245	94
CSP	0.23	0.000245	94
Wind	0.17	0.00189	69
Geothermal	0.25	0.00174	56
Biomass	0.21	0.0149	56
Oil	0.11	1.69	30
Coal	0.11	1.08	32

Table 7
Scoring scale of relative priorities (Saaty, 1987).

Scale	Degree of Preference
1	Same significance
3	Weak significance
5	Strong significance
7	Very strong significance
9	Extreme importance
2, 4, 6, 8	Intermediate value

and professionals in energy sector): 10 researchers in energy field (5 from Moi University and 5 from University of Nairobi), 30 experts in energy sector (10 from Ministry of Energy; 10 from Kenya Power and Lighting Company — KPLC and 10 from Rural Electrification Authority — REA). Therefore, the weights were determined by AHP method as follows:

Step 1- *Comparison matrix establishment:* This matrix is made of the results of pairwise comparison from the survey. This comparison reflects how two elements (criteria or sub-criteria) with a common parent in the hierarchy relate each other (i.e. element “*a*” is extremely important to element “*b*”).

Step 2- *Weights determination:* After a comparison matrix is established, a weighting vector of “*k*” element is calculated by Eq. (1).

$$w_k = \frac{1}{n}\sum_{j=1}^{n}\left({}^{a_{kj}}/_{\sum_{i=1}^{n} a_{ij}}\right)(k = 1, \ldots\ldots, n) \tag{1}$$

Where *i*, *j* and *n* ($n = m \times p$ *if i=1, …., m and j=1,…; p*) are respectively row, column and dimension of the comparison matrix and a_{ij} is the matrix element of row *i* and column *j*.

Step 3- *Consistency Check*: The comparison matrix obtained is reasonable in case there is consistency (Ishizaka and Labib, 2009; Saaty, 1987; Stojanovic, 2013). Hence, a consistency index (*CI*) is given by Eq. (2).

$$CI = {}^{(\lambda_{\max}-n)}/_{(n-1)} \tag{2}$$

Where $\lambda_{\max}$ is maximal eigenvalue.

Then, the consistency ratio (*CR*) is obtained by applying Eq. (3).

$$CR = {}^{CI}/_{RI} \tag{3}$$

Where *RI* is called random index. Table 8 shows calculated *RI* for different matrix dimensions.

Hence, the matrix is called consistent if $CR \leq 10\%$ (Ishizaka and Labib, 2009; Saaty, 1987; Stojanovic, 2013).

Therefore, the problem can be modeled using the structure shown by Fig. 1.

2.4.2. *Ranking of energy alternatives*

After the weights were determined by the AHP method, the TOPSIS was used to rank different technologies. Fig. 2. shows the flowchart of the hybrid AHP–TOPSIS method used A detailed methodology of TOPSIS can be found in Roszkowska (2011). The model is conducted as described below.

After “*m*” alternatives, “*n*” attributes (sub-criteria) and score of “*m*” with respective to each “*n*” are identified:

- Let x_{ij} be the score of alternative *i (i =1,………, m)* with respect to sub-criterion *j (j=1,……, n)* and v_{ij} be the overall weights for each sub-criteria;
- The matrix $\boldsymbol{X} = (x_{ij})$ $m \times n$ *matrix* was constructed ($m \times n =$ *matrix order*). Here, the matrix elements x_{ij} are the data values of the different sub-criteria.

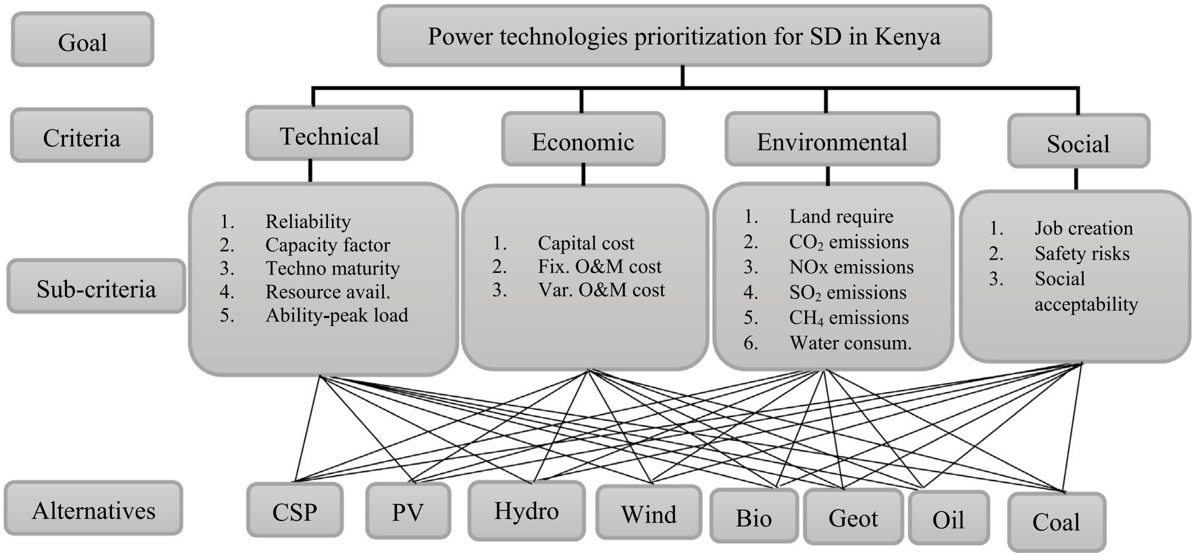

Fig. 1. Flowchart of energy technologies ranking using TOPSIS.

Table 8
Saaty *RI* values (Saaty, 1987).

Matrix order-n	1	2	3	4	5	6	7	8	9	10
RI	00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

Stage 1- Normalization of x_{ij} Eq. (4).

$$r_{ij} = x_{ij} / \sqrt{\sum_i \left(x_{ij}^2\right)} \tag{4}$$

Stage 2- Weighted Normalized of x_{ij} Eq. (5).

$$v_{ij} = v_j \times r_{ij} \tag{5}$$

Stage 3- Negative Ideal Solution Eq. (6).

$$A^- = \left\{w_1^-, \ldots\ldots\ldots, w_n^-\right\} \tag{6}$$

$$w_j^- = \left\{\min(v_{ij}) \text{ if } j \in J^+, \max(v_{ij}) \text{ if } j \in J^-\right\}$$

Stage 4- Ideal Solution Eq. (7).

$$A^+ = \left\{w_1^+, \ldots\ldots\ldots, w_n^+\right\} \tag{7}$$

$$w_j^+ = \left\{\max(v_{ij}) \text{ if } j \in J^+, \min(v_{ij}) \text{ if } j \in J^-\right\}^+$$

Stage 5- Separation from Negative Ideal Solution Eq. (8).

$$S^- = \left[\sum_j \left(w_j^- - v_{ij}\right)^2\right]^{\frac{1}{2}} \tag{8}$$

Stage 6- Separation from Ideal Solution Eq. (9).

$$S^+ = \left[\sum_j \left(w_j^+ - v_{ij}\right)^2\right]^{\frac{1}{2}} \tag{9}$$

Stage 7- Relativeness Closeness to Ideal Solution ($0 < Ci^* < 1$) Eq. (10).

$$Ci^* = {}^{S^-}/(S^+ + S^-) \tag{10}$$

2.4.3. Scenarios analysis

In order to analyze how results behave with the change of input data, a sensitivity analysis was performed. The results (ranking) are said robust in case they do not vary with the change of input parameters (Ishizaka and Labib, 2009). Therefore, different scenarios were evaluated for this effect.

3. Results and discussion

3.1. Weight of criteria and sub-criteria

After experts' feedback was obtained using Saaty's scoring scale, pairwise comparison matrixes among criteria and among sub-criteria were constructed. By applying AHP method, normalized weights for the different criteria and sub-criteria were obtained by using Eq. (1). The constructed matrixes are the square matrixes. Hence, the dimension of matrix of the criteria is $n = 4$ (pair-wise comparison matrix among the four criteria). For Sub-criteria, $n = 3$ for Economic sub-criteria, $n = 5$ for Technical sub-criteria, $n = 6$ for Environmental sub-criteria and $n = 3$ for Social sub-criteria. The elements x_{ij} of the matrixes are made of the scores obtained in a pair-wise comparison using scoring scale of Saaty. The scores resulted from the experts' feedback. Hence, it was possible to calculate the normalized weights of different established matrixes: weight for each criterion deduced from the comparison matrix of the criteria (Technical, Economical, Environmental and Social) and weight for each sub-criterion deduced from the three comparison matrixes among sub-criteria. The consistency ratios for each constructed pairwise comparison matrix were calculated using Eq. (2) and Eq. (3) and checked if their values are lower than 10%. All matrixes were found consistent. Figs. 3 and 4 show obtained weights for criteria and sub-criteria, respectively.

From the results for normalized weights, technical and economic criteria have the highest weights in comparison to other criteria with the weights of 45.64% and 30.32% respectively. Environmental and social dimensions are found with the weights of 14.61% and 9.44% respectively. This is due to the fact that respondents gave a higher preference for resources availability, technology reliability and capacity factor. The economic criteria made of required capital and O&M costs was weighted the second and this may be explained by the fact that securing investments is an obstacle as access to capital is one of the major barriers to implementation of energy projects in African countries (Muzenda,

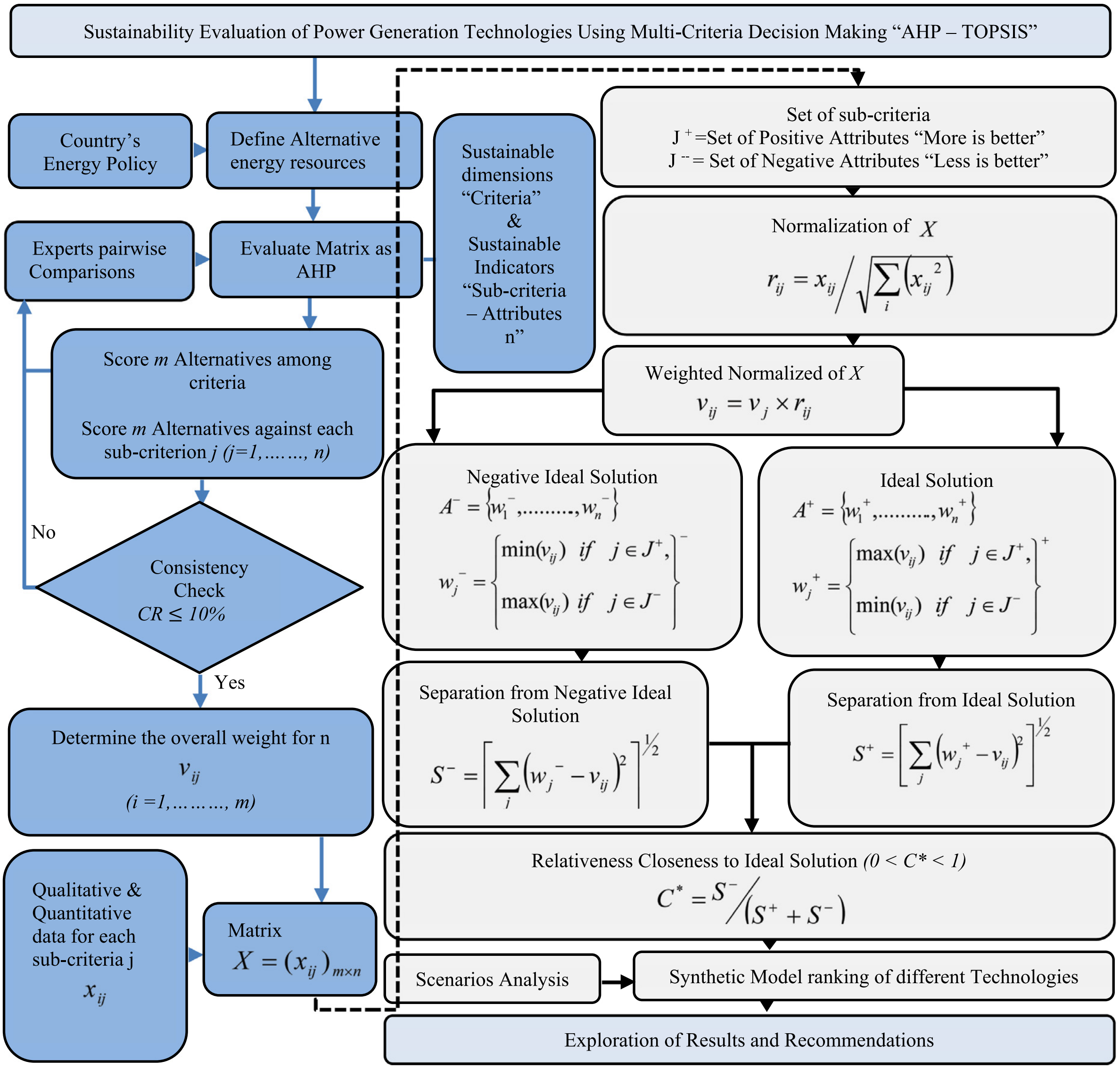

Fig. 2. Detailed flowchart of sustainability evaluation of power generation technologies using MCDM "AHP–TOPSIS"..

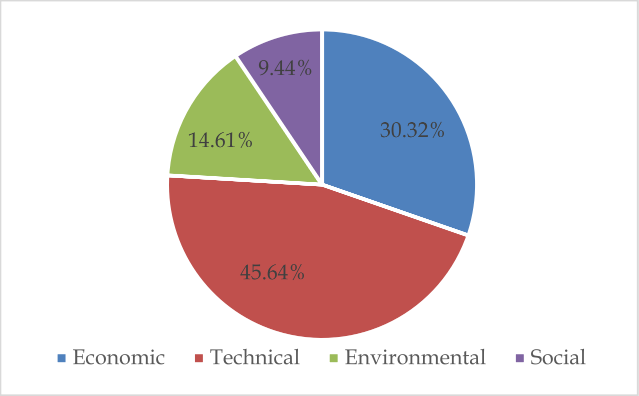

Fig. 3. Normalized weights for criteria.

2009). Hence, technical and economic aspects were most preferred by respondents than the other sustainable dimensions (social and environmental). The environmental criteria, with the weight of 14.61%, came in the third position before the social criteria with 9.44% of weight.

3.2. Evaluation of alternatives

After the weights for the different criteria and sub-criteria were obtained, overall weights of each sub-criteria with regard to criteria were thereafter determined (Fig. 5). Matrix of sustainable indicators values was constructed by taking the values (or average) of sustainable indicators "sub-criteria" presented in Tables 3–6 where the matrix elements are the indicators for the different power technology options in Kenya. Therefore, the TOPSIS method was applied to the matrix made by the 17 sustainable indicators for the 8 alternatives as shown by Fig. 6, following the steps of Eqs. (4) to (10).

The Relativeness Closeness to Ideal Solution Ci* was then determined (Fig. 7). This helped to rank the different technologies (Table 9).

With regards to respondents' criteria weights, RE (Solar PV, Wind and CSP) occupy the first positions. The most sustainable power technology is solar PV with a higher priority. This technology has the highest resource potential in Kenya and it has the lowest capital and O&M costs compared to other technologies.

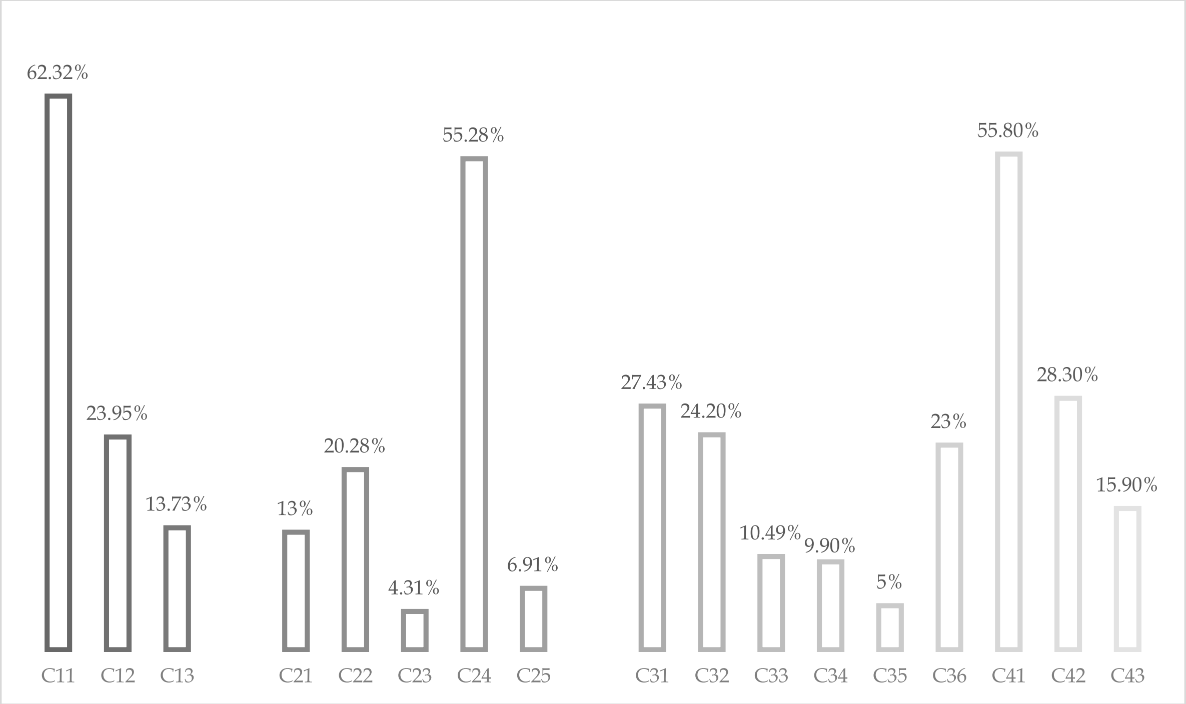

Fig. 4. Normalized weights for sub-criteria.

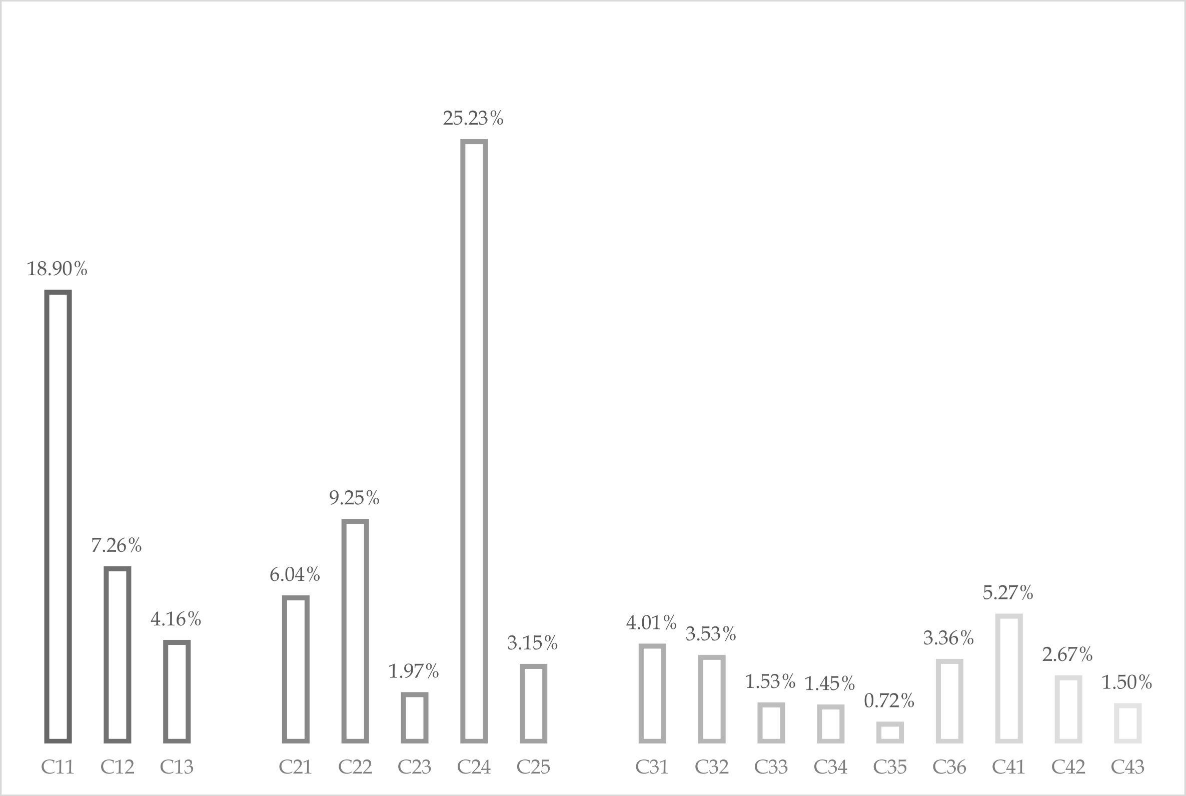

Fig. 5. Sub-criteria overall weights with regard to criteria.

3.3. Scenario analysis

Although the results obtained show a higher policy preference of solar PV, CSP and Wind in first positions respectively, there may raise arguments concerning this outcome due to input values in the analysis. Therefore, input data (likely to vary) were analyzed by performing a scenarios analysis.

According to Schnaars, scenarios analysis is a prevalent method of looking at future business environment (Schnaars, 1987). This is an important technique which can be used in trying to identify

$$\left[\begin{array}{c|cccccccccccccccccc} & c_{11} & c_{12} & c_{13} & c_{21} & c_{22} & c_{23} & c_{24} & c_{25} & c_{31} & c_{32} & c_{33} & c_{34} & c_{35} & c_{36} & c_{41} & c_{42} & c_{43} \\ Hydro & 1975 & 40 & 2 & 4 & 52.5 & 5 & 25 & 2 & 750 & 11 & 0.032 & 0.0155 & 0 & 67.5 & 0.27 & 0.945 & 68 \\ PV & 900 & 11.5 & 0 & 2 & 27.5 & 4 & 23000 & -1 & 35 & 49.174 & 0.178 & 0.257 & 0 & 1 & 0.87 & 0.000245 & 94 \\ CSP & 7545 & 77.5 & 0 & 2 & 53.5 & 3 & 15400 & 1 & 40 & 16 & 0.068 & 0.042 & 0 & 3.02 & 0.23 & 0.000245 & 94 \\ Wind & 1250 & 33.25 & 0 & 4 & 46.5 & 5 & 1800 & -1 & 100 & 22 & 0.065 & 0.055 & 0 & 0 & 0.17 & 0.00189 & 69 \\ Geother & 5275 & 13.5 & 16.5 & 5 & 85 & 4 & 87.6 & 1 & 18 & 18.913 & 0.28 & 0.02 & 0 & 156 & 0.25 & 0.00174 & 56 \\ Biomass & 2850 & 50 & 10 & 4 & 82.5 & 4 & 3.61 & 0 & 5000 & 69.25 & 0.89 & 0.485 & 40 & 134.25 & 0.21 & 0.0149 & 56 \\ Oil & 975 & 16.5 & 3.875 & 4 & 52.5 & 5 & 65.09 & 2 & 2.5 & 715 & 1 & 4.425 & 8 & 78 & 0.11 & 1.69 & 30 \\ Coal & 650 & 10 & 10 & 4 & 73 & 3 & 162.82 & 0 & 2.5 & 855 & 2.1 & 3.365 & 5.5 & 78 & 0.11 & 1.08 & 32 \end{array}\right]$$

Fig. 6. Matrix of sustainable indicators values (Matrix order $n = 8$ alternatives $\times 17$ sustainable indicators).

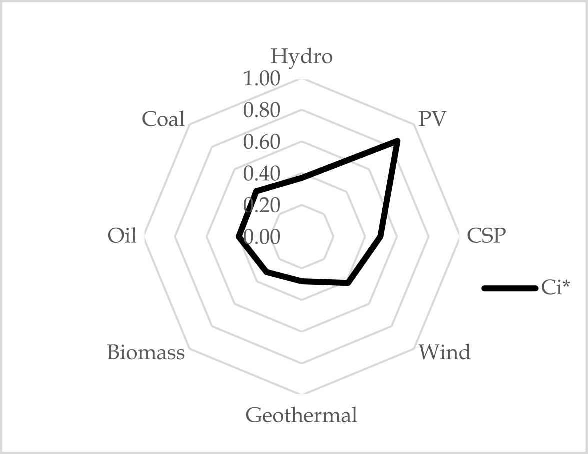

Fig. 7. Relativeness closeness to ideal solution.

Table 9
Technologies prioritization based on respondents criteria weights.

Alternative	Rank
Hydro	6
PV	1
CSP	2
Wind	3
Geothermal	8
Biomass	7
Oil	5
Coal	4

possible future situations (Schnaars, 1987). In energy sector, various developed scenarios provide an important support to decision makers and the results are dependent on input data derived from assumptions (Weimer-Jehle et al., 2016). In that regard, this study sought of finding a most (or least) promising technology in case one or the other sustainable dimension may be given more importance by decision makers than another. Therefore, scenarios were performed by varying the weights of the sustainable dimensions. Some assumptions regarding the weightage of the main criteria were considered. The analysis was performed by assuming that a privileged criterion is subject to being given a weight which is double of the others' whereas equal weight was considered by assuming equal importance for all the criteria. Hence, five distinct scenarios cases were analyzed: economic criteria most privileged, technical criteria most privileged, environmental criteria most privileged, social criteria most privileged and criteria given same importance.

3.3.1. Scenario 1: Technologies weighted for economic scenario

In this scenario, economic criterion was considered as the most privileged dimension compared to others. A weight of 40% was given to this indicator while the three other criteria shared the 60%. Here, minimal Capital and O&M costs were considered as most important indicators to be privileged. This scenario is illustrated on Fig. 8.

In this scenario, Solar PV, Wind and Coal are respectively the most economic technologies in Kenya while CSP is the least.

3.3.2. Scenario 2: Technologies weighted for technical scenario

In this scenario, technical criterion was considered as the most important compared to other dimensions and was given a weight of 40% while others shared the remaining 60%. Here, an emphasis was given to maximal capacity factor, reliability, technology maturity, ability to respond to peak load and resources availability. This scenario is illustrated on Fig. 8.

In this scenario, Solar PV, CSP and Wind are respectively the most technically suitable technologies in Kenya while Biomass is the least.

3.3.3. Scenario 3: Technologies weighted for environmental scenario

In this scenario, the environmental dimension was privileged with respect to other dimensions and was given a weight of 40% while others shared the remaining 60%. Here, an emphasis was given to a technology with minimal land requirement and least pollution emissions and water consumption. This scenario is illustrated on Fig. 8.

In this scenario, Solar PV, Wind, CSP are respectively the most environmental friendly technologies in Kenya while Biomass is the least.

3.3.4. Scenario 4: Technologies weighted for social scenario

In this scenario, the importance was given to a technology with a high job creation potential and social acceptability. The social criterion was then considered as the most important compared to other dimensions and was given a weight of 40% while others shared the remaining 60%. This scenario is illustrated on Fig. 8.

In this scenario, Solar PV, Wind and CSP are respectively the most social technologies in Kenya.

3.3.5. Scenario 5: Equal weighted technologies scenario

In this scenario, all dimensions were treated equally and each criterion was then given a weight of 25%. This scenario is illustrated on Fig. 8.

If the sustainable dimensions are treated equally, Solar PV, Wind and CSP are respectively the most promising technologies in Kenya while Biomass is the least.

It is clear that RE (especially Solar PV, Wind and CSP), Biomass excluded, always occupy first positions in most all scenarios. Solar PV technology is found the most sustainable technology in Kenya compared to other technologies. With a massive exploitation of fossil fuels considered in this study (available reserves were considered to be totally exploited in the next 20 years), they are not found to compete with RE (especially Solar PV, Wind and

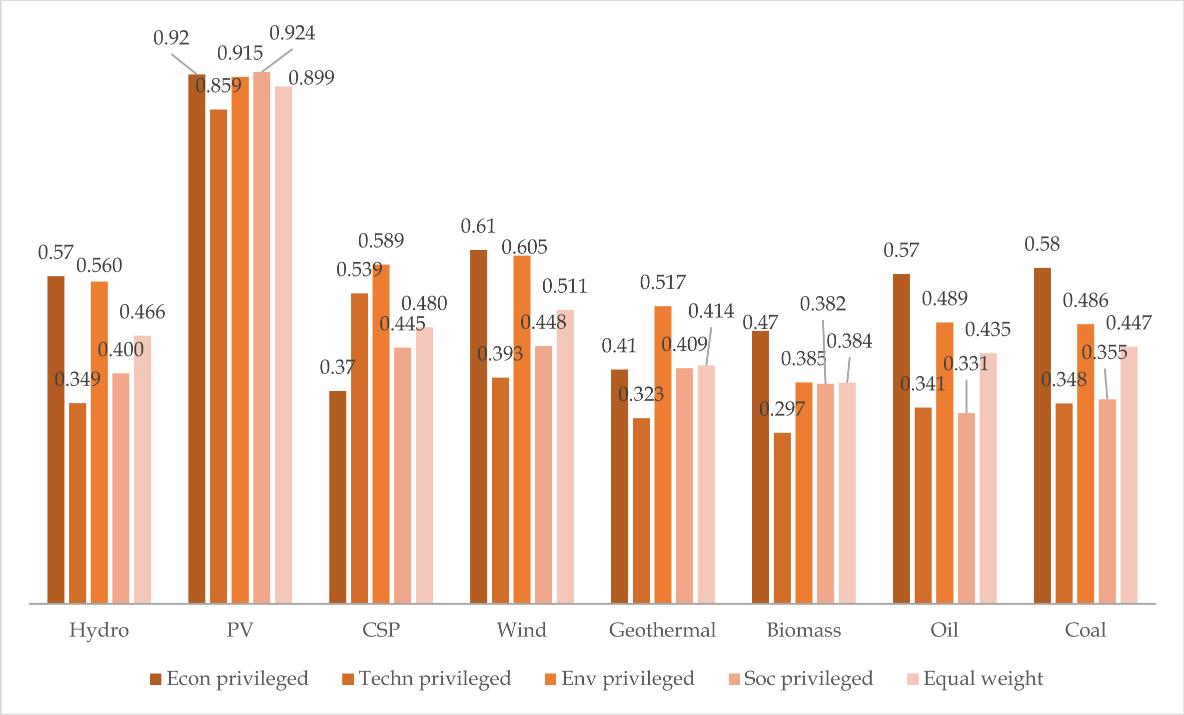

Fig. 8. Scenarios analysis with regard to criteria.

CSP) in all the scenarios, except in economic scenario where CSP occupies the last position.

Therefore, the high deployment of RE technologies in Kenya will not harm its economic growth. The results obtained in this study come to reinforce Kenyan government strategies for its energy mix policy (Ministry of Energy, 2018).

4. Conclusions

This study aimed at prioritizing power technology options in Kenya based on available energy resources in order to solve the dilemma of most sustainable technologies in Kenyan energy mix model. Eight technologies were found to be the options in Kenya: Geothermal, Hydropower, Biomass, Wind, Solar PV, CSP, Coal and Oil. In order to rank the different alternatives in sustainable way, multi-criteria decision making method was applied. Therefore, 17 sustainable indicators were used after consultation of some energy experts in the country. By applying the hybrid AHP–TOPSIS model, the results showed that renewable energy technologies (especially Solar PV and Wind) are ranked higher than fossil fuels with first priority given to Solar PV. Five scenarios were performed by varying the weights of the sustainable dimensions. By privileging economic criteria, Solar PV, Wind and Coal are respectively found the most economic technologies in Kenya while CSP is the least. By privileging the technical criteria, Solar PV, CSP and Wind are respectively the most technically suitable technologies in Kenya while Biomass is the least. In case the environmental criteria are privileged, Solar PV, Wind, CSP are respectively the most environmental friendly technologies in Kenya while Biomass is the least. In scenario where the social dimension is privileged, Solar PV, Wind and CSP are respectively the most social technologies in Kenya. In case the all sustainable dimensions are treated equally, Solar PV, Wind and CSP are respectively the most promising technologies in Kenya while Biomass is the least. With different scenarios performed, Fossil fuels and Biomass were found to have a fragile sustainability performance in Kenya; with a massive exploitation of fossil fuels considered in this study (available reserves considered to be totally exploited in the next 20 years), they did not compete with those RE technologies. This would give them a low chance for energy market integration in Kenya, especially for investors in energy projects. However, due to intermittency of RE technologies, these fossil fuels would help to maintain the reliability of Kenyan power supply in their energy mix model. Although CSP has not been privileged by Kenyan policymakers, it ranked among the first three promising technologies, except for economic scenario. This study would help the Kenyan energy policy-makers, investors as well as energy projects' investors in Kenya to have an understanding of sustainable power technologies when planning for future energy projects.

Therefore, this study would recommend the Kenyan government and energy investors to put much efforts in exploiting RE energy resources. Hence, due to their intermittencies (especially Solar and Wind), their combination in hybrid systems would alleviate this concern.

This study made its assumptions that no more reserves of fossil fuels will be discovered in future. Hence, any additional discovery may change the prioritization of the results found. Furthermore, some data availability in local context were an obstacle and data from similar projects conducted in other countries were considered which may differ from local situation. Hence, future research by using local data would give robust results.

At last, this study assumed that power generation is only to be supplied by local power plants. The influence of imports and exports were neglected. This study also recommends future research to incorporate spatial and temporal change of sub-criteria as some indicators (e.g. LCOE) are expected to vary in future.

CRediT authorship contribution statement

Egide Manirambona: Conceptualization, Investigation, Formal analysis, Methodology, Writing. **Stephen M. Talai:** Supervision, Investigation, Formal analysis, Validation, Reviewing and editing. **Stephen K. Kimutai:** Supervision, Investigation, Formal analysis, Validation, Reviewing and editing.

Declaration of competing interest

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

Data availability

The data that has been used is confidential.

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