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Sustainability indicators for renewable energy systems using multi-criteria decision-making model and extended SWARA/ARAS hybrid method

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ABSTRACT

This paper presents new results on the assessment of sustainability indicators for renewable energy (RE) systems (solar PV, wind, phosphoric acid fuel cell, and solid oxide fuel cell). Multi-criteria decision-making (MCDM) model and hybrid Step-wise Weight Assessment Ratio Analysis/Additive Ratio Assessment (SWARA/ARAS) method are used in this study. Five sustainability criteria (resource, environmental, economic, social and technology) and fourteen sub-categories (area, material, energy-construction, energy-fuel, CO_2-construction, CO_2-fuel, capital-construction, capital-fuel, delivered cost of energy, current installed capacity, growth rate, capacity factor, system efficiency, and lifetime) are included in this analysis. The extended SWARA and ARAS hybrid method in addition to three energy experts are used in this study for the calculation of sustainability indicators. The final result of this process of ranking the four renewable energy technologies using SWARA-ARAS hybrid method based on the five sustainability criteria and the fourteen subcategories is: (1) wind energy systems (land-based), (2) solid oxide fuel cell, (3) phosphoric acid fuel cell, and (4) solar energy systems (poly-silicon). The MCDM model integrated with the hybrid SWARA/ARAS method is found to be a useful methodology for the sustainability assessment of renewable energy systems, sustainable energy development and decision-making for policy makers.

1. Introduction

One of the biggest challenges in the world at present is the enormous and fast growing in world population (9 billion by 2050), technology, development, and civilization which is correlated with the huge demand and excessive consumption patterns of energy, water, and food resources compared to energy production and the limited natural land, water, materials, and fuels resources. In addition to that, there are extensive destructions caused to the environment and there is a lack of optimization between production, consumption, and environment protection [1]. Therefore, the need for clean environment and for economic, energy, food, and water security became in the last century a source of real concern instead of being the source of life fulfillment for world communities. This is mainly a consequence of the extensive, uncontrolled, consumption and irresponsible actions inflicted by the human being. These challenges are not new to the human being and the environment. Recently, in international as well as in research communities, they have come to be addressed under the label “Water, Energy, and Food Security Nexus” [2]. “Water, Energy and Food Security Nexus” is a rubric that reflects the deep interconnection between these three life essentials and the strain that governs them at the same time. In other words, it implies that action in one of the three systems has impacts on the other two as well as on climate change and the ecosystem [3]. There is a crucial need for an integrated solution, which will optimize between the three aspects (energy, water, and food) in terms of production and consumption. The demands for energy, water, and food are projected to increase by 2030 by 50%, 30%–40%, and 35%–40%,

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Nomenclature

MCDM	Multi criteria decision making
$\bar{t}_j$	Average attribute rank value of the ***j***th criterion
r	Number of experts
t_{jk}	Ranking of the ***j***th criterion by the k^{th} expert
$\boldsymbol{t_{j,f}}$	Final attribute rank
s_{jh}	Comparative importance of different attributes
$\sum_{j=1}^{n} t_{j,f}$	Summation of the final ranks of the evaluation criteria
n	Number of the evaluation criteria
σ^2	Dispersion of experts' ranking
β_j	Variation of experts' ranking
W	Coefficient of concordance of the experts' views
S	Total square deviation of the rankings of each attribute
$\sum_{k=1}^{r} t_{jk}$	Summation of the rankings by all experts for each j^{th} criterion
T_k	Index of reiterated ranks in the r rank
$\chi^2_{\alpha,\nu}$	Significance of the coefficient of concordance
α	Level of significance
ν	Degrees of freedom
χ^2_{tbl}	Critical tabular value in the statistical tables
q_j	Recalculated weight
w_j	Relative weight of the criteria
x_{aj}	Overall performance rating of the a^{th} alternative with respect to the j^{th} criterion
x^k_{aj}	Rating of the a^{th} alternative with respect to the j^{th} criterion from the k^{th} expert
x_{0j}	Optimal performance rating with respect to the j^{th} criterion
$x_{aj,N}$	Normalized performance rating of the a^{th} alternative with respect to the j^{th} criterion
$\sum_{a=1}^{m} x_{aj}$	Summation of the overall performance ratings of all alternatives with respect to the j^{th} criterion including the optimal performance rating
m	Number of alternatives
w^r_{ij}	Resultant weight of the i^{th} sub-criterion from the j^{th} main criterion category
w_{ij}	Calculated weight of the i^{th} sub-criterion from the j^{th} main criterion category
$\sum_{i,j} wj\, w_{ij}$	Summation of the multiplication of the weight of each sub-criterion with the weight of its main criterion category for each i^{th} sub-criterion and j^{th} main criterion
υ_{aj}	Weighted normalized performance rating of the a^{th} alternative with respect to the j^{th} criterion
w^r_{ij}	Resultant weight of the i^{th} sub-criterion from the j^{th} main criterion category
$x_{aj,N}$	Normalized performance rating of the a^{th} alternative with respect to the j^{th} criterion
S_a	Overall performance index of the a^{th} alternative
$\sum_{j=1}^{n} \upsilon_{aj}$	Summation of the weighted normalized performance rating of the a^{th} alternative with respect to all evaluation criteria
Q_a	Degree of utility of the a^{th} alternative
S_0	Overall performance index of the optimal alternative

respectively [1,4]. The correlation between water, food, and energy and their effects on the environment are quite palpable in daily life. For example, water extraction for purposes of distribution and treatment cannot be done without the consumption of excessive amounts of energy. On the other hand, energy production through different power generation technologies requires considerable amounts of water (steam turbine engines and most of the renewable power systems). Also, food production, elaboration, storage and transportation from farms and marine sectors are dependent on energy availability and security (Fig. 1). It is estimated that the food sector accounts for around 30% of global energy consumption [1,3,and4]]. Furthermore, food production systems are not only heavily dependent on energy resources, but also depend significantly on water and land resources as well as on the contribution to the global greenhouse gas emissions directly and indirectly [3].

All the concerns for the needed balance between the three sectors (water, energy, and food) and for the social tensions on the local and global levels can be minimized and controlled by developing integrated and sustainable solutions based on the interconnections of these sectors. These solutions start with the focus on energy production systems since it represents the baseline for not only food and water sectors, but also the environment and climate change dilemma around the world. Sustainability means maintaining change, consumption, or production in a balanced pattern between different life aspects, sequent generations, nature, and different living creatures. This concept is a subject of debate about human aspirations at present and life fulfillment for future generations [5–7]. Worldwide communities and environmental agencies have assigned three main aspects to the concept of sustainability, which can be summarized in the aspiration to maintain a balance between consumption and production in relation to the environment, economy and social resources in the long term [7,8]. Sustainability is evaluated through different rational indicators to reflect the performance of the assessed system with respect to the environment, economy, resources, technology, and society. Energy security has become the focal point of extensive research efforts around the world, not only due to its great effect on the global climate change argument and on the best part of environmental concerns, but also due to its substantial role in water and food security fulfillment. Moreover, recently, conventional energy resources around the world have become increasingly vulnerable to depletion with the increment in energy demand compared to production. Therefore, the need for clean, sustainable, economically effective, and efficient energy production systems became in the last century a major concern and a challenging goal. The energy production sector (especially electricity generation) in all parts of the world was mainly dependent on the use of fossil fuels (coal, natural gas, and oil). The global dependence on fossil fuels is attributed to their advantages of having high energy-density, being easily transportable and being able to generate a large amount of power in a compact plant that uses a relatively small land area. However, in the coming years, the reliance on fossil fuels will diminish due to: (1) The huge amounts of greenhouse gas emissions (CO_2, NO_x, and SO_x) produced upon their combustion, which violates the new global emissions regulations – reduction of these gases; (2) the depletion of fossil fuel reserves; and (3) the reduction of the dependency on foreign imports by using local and available resources. It is also noted that the world energy demand is expected to triple by 2050 [1]. The greenhouse gas emissions from fossil fuels combustion have several negative effects on the climate, including

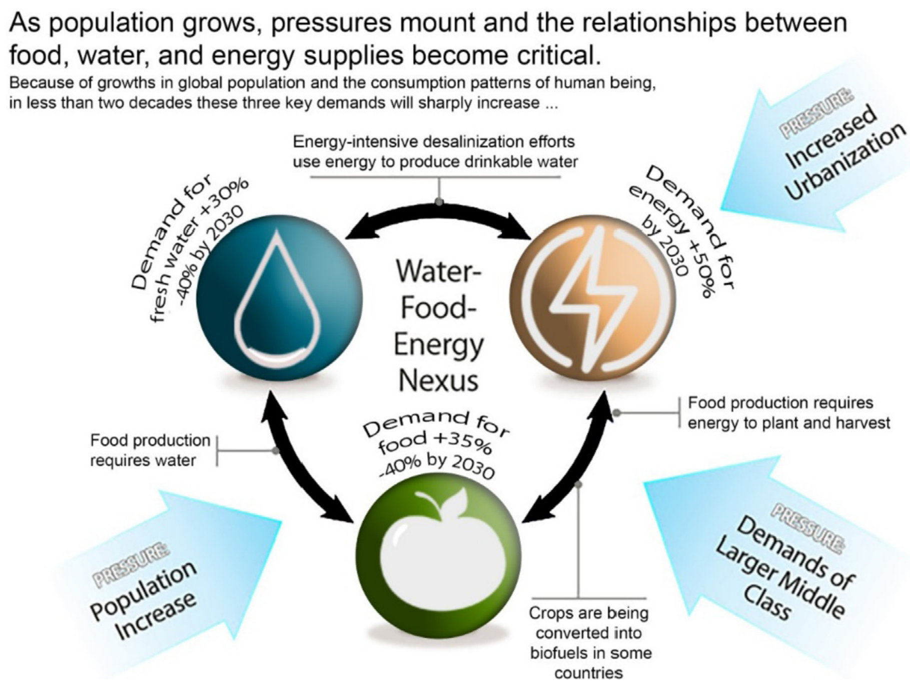

Fig. 1. Water-food-energy nexus.

floods, hurricanes, and other natural disasters. Greenhouse gases are represented by SO_x, NO_x, CO, and CO_2. One of the effective ways to mitigate CO_2 emissions to the atmosphere from fossil-fueled power plants is the capture and storage of carbon via absorption and adsorption. This process is done by using gas absorbents such as amino acid salt solutions, which are considered as promising CO_2 absorbents. This is mainly due to their advantage of having low evaporation and fewer degradation issues compared to other amine solutions. Also, they can be used as blends with other liquids to enhance the absorbance of CO_2. Amino acid salt solutions are produced through the reaction between amino acids and alkaline substances. There are different types of Amino acid salt solutions with different CO_2 loading based on the thermo-chemical, physical, absorbance, and CO_2 solubility properties. In power plants, there are three technologies of capturing and storing carbon, which in turn will significantly reduce CO_2 emissions to the atmosphere. There are pre-combustion, oxy-fuel combustion, and post-combustion capturing technologies. The absorption/adsorption via amino acid salt solutions is considered as post-combustion capturing technology. The integration of carbon capturing technology with fossil-fueled power plants produces about 400–450 MW net electricity and a rate of 90% carbon capture. Zhang et al., 2018 explained in their review the effectiveness of amino acid salt solutions as carbon capturing technology, thermodynamics, kinetics, and the different applications of the technology in addition to the reduction of greenhouse gas emissions to the atmosphere [9]. A novel approach, which has attracted researches attention in recent decades to enhance CO_2 absorption process is the usage of nano-fluids. CO_2 absorption enhancement system using nano-fluid was considered as a committed technology for air pollution mitigation. Furthermore, the usage of nano-fluids as solvents for CO_2 absorption will significantly reduce energy cost expenses by these processes. The enhancement of absorption rate is influenced by several key factors such as the type of nanofluid, size of the nanoparticle, volume concentration, pressure, temperature, and the initial concentration of CO_2. Extensive literature review about CO_2 absorption using nano-fluids was conducted by Zhang et al., 2018 [10]. This environmental pressure caused by the continuous generation of greenhouse gas emissions is affecting future energy production. Searching for sustainable solutions to resolve these severe consequences led to the development of renewable and alternative energy extraction systems from nature at different levels of sustainability. Nuclear and renewable energy production systems are clean and are alternative ways to produce electrical power. Nuclear power technologies are designed to generate electricity from the nuclear reactions of the radioactive elements uranium and plutonium as fuels [1,11]. Nuclear power plants generate no emissions to the environment during operation (clean power systems), but there are several safety issues associated with their long-term, continuous operation (accidents and terrorist threats) and the management of the spent fuel generated during the process. Furthermore, the fuel (Uranium) used in the nuclear power plant is not renewable. The fuel is also available only in some parts of the world (example: Canada, Australia, and Ukraine) [1,12]. The second alternative to fossil fuel power generation is renewable energy technologies which use natural energy obtainable from the sun, wind, hydro (water), ocean (wave, tidal, marine current power, and ocean energy thermal system), geothermal (core of the earth) and biomass resources. Up to 80% of the projected energy demand by 2050 can be generated from renewable resources [1]. However, the intended world dependence on renewable power systems, together with the continued increase in energy demand and the inevitable depletion of fossil fuels impose the necessity for all energy producers and researchers to focus more on sustainability aspects of the power production systems than on development. Renewable power production technologies vary significantly in terms of power conversion efficiency, operation parameters, environmental effects, land requirements, capital costs, lifetime, material and manufacturing requirements. In other words, they differ on the level of sustainability, which is the main scope of this paper, as will be detailed [13–15]. Caliskan [16] and Fudholi et al. [17] developed a sustainability index for a solar collector and a solar PV thermal collector, respectively. A sustainability index for the solar collector and solar PV/thermal collector were proposed using energy, exergy, environmental, enviroeconomic, exergoenvironmental (EXEN), and exergoenviroeconomic (EXENEC) analysis as a result of taking environmental conditions into consideration. Raza et al. [18] developed a sustainability index approach based on technical, economic and environment criteria for the selection of three energy storage systems (lithium polymer batteries, fuel cell, and lead acid batteries) for intermittent and renewable energy resources (solar and wind). A new weighted approach was used to determine the sustainability index of the energy storage systems. Fuel cell was selected as the best energy storage option based on the sustainability index developed in this study. Papilo et al. [19] developed sustainability indicators for palm-oil based bioenergy. In their study, they used ten indicators for the environmental, social and economic factors. The results obtained for bioenergy development show that there is a need to balance the three aspects and each indicator of sustainability.

Recently, several research efforts have been performed to evaluate the sustainability of different renewable power systems and energy storage systems against a range of sustainability indicators using different approaches and engineering management methods. Multi-criteria decision-making methods are well used to serve this purpose. Guzmána et al. [20] performed a life cycle analysis using MCDM for the sustainability evaluation of renewable energy technologies. Three environmental criteria were used for this study: climate change, resources, and ecotoxicity. For the social aspect, the creation of employment, beneficiary population (%) and expected mortality in an accident were used. For the economic aspect, the cost of operation and maintenance, cost of capital and energy cost were used in this analysis. In addition to that, the availability of resources such as solar and wind and the related technical aspects (distance, weight, nominal power, and height) were included in the technical-political dimension. A comprehensive analysis using MCDM method for distributed energy systems was performed by Xu et al. [21]. The main objective of this study was to develop a comprehensive framework for sustainability prioritization of distributed energy systems. The MCDM method was combined with an interval Decision-making Trial and Evaluation Laboratory (DEMATEL) and the interval VIKOR method. A Gas turbine system, a fuel cell system, a photovoltaic system, and an internal combustion engine system were used in this study. The results showed that the photovoltaic system was recognized as the most sustainable scenario, followed by fuel the cell system, the gas turbine system, and the internal combustion engine system. Recently, Baumann et al. [22] has reviewed the MCDM approaches for evaluating energy storage systems (ESS) for renewable-based energy systems. The main objective of the study was the selection of suitable and sustainable EES using MCDM method for grid-tied renewable power systems. The technological, economical, societal, and environmental aspects were included in this analysis.

A multi-criteria decision-making model was used in Zhang et al. study [23] for optimal site location selection of ocean thermal energy conversion (OTEC) system. The model was based on sixteen sustainability criteria and seven groups of experts. The model was tested by a case study using a sensitivity analysis to demonstrate the robustness and the effectiveness of the proposed method. The results showed that this method was effective for decision-making based on sustainability criteria and for the selection of the appropriate location of the OTEC energy system. Hacatoglu et al. [24] developed an integrated multi-criteria decision making sustainability model based on socioeconomic and environmental criteria to assess the waste to energy technologies such as incineration, gasification, pyrolysis, and anaerobic digestion. This method was used to select the suitable and sustainable technology for waste to energy conversion and demonstrated by a case study in the city of Behbahan in Iran. The results show that the final ranking of all the waste to energy technologies from the most to least preferable as: Anaerobic digestion, Gasification, Pyrolysis, and Incineration. Wang and Huang [25] used a theoretical analysis based on stochastic models to investigate the investment and operation of micro grid renewable energy systems. The optimal investment decisions related to the integration of renewable power system and the storage capacities and the best demand response strategies regarding the pricing and power scheduling were determined. The advantage of using a mixed renewable energy model (for the prediction error of renewable energy generation) and demand response in terms of reducing investment cost of the microgram power system was demonstrated in this study. Hacatoglu et al. [26] and Hacatoglu [27] developed an integrated sustainability index for energy systems using multidimensional sustainability criteria. The sustainability indicator was determined using normalization, weighting, and aggregation of sustainability indicators. The system was applied for both stand-alone and hybrid power systems in southern of Ontario in Canada. Solar PV-hydrogen power system was the best hybrid system compared to the other tested systems with respect to the sustainability indicator. The results also show that the climate change and ozone layer depletion indicators, affordability, commercial viability, and land area have the strongest effect on the integrated sustainability indicator. The results obtained in the course of this study show that the integrated sustainability indicator was a useful decision analysis tool for forecasting single or hybrid sustainable energy systems.

In this paper, a multi-criteria decision-making model integrated with a new SWARA/ARAS hybrid method is used. The originality of this study is the use of Multi Criteria Decision-making Model and an extended SWARA/ARAS Hybrid Method with the input from energy experts to evaluate the importance of the sustainability indicators of renewable power systems (polysilicon solar PV energy, solid oxide fuel cell, phosphoric acid fuel cell, and onshore wind energy systems). The new proposed approach is based on the improved SWARA method combined with the ARAS method. The SWARA method is a new subjective criteria-weighing method with a wide application in various fields such as economics, management, industry, manufacturing, design and architecture, policy and environmental sustainability. It builds its procedure on implicit knowledge, experience, and ideas of experts about a specific topic and it can be described as a numerical representation of their experience [28]. Hashemkhani et al. [29] applied an additional step to the classic SWARA methodology to improve the criteria prioritization process and make it more objective; they named it as Extended Step-wise Weight Assessment Ratio Analysis [29]. Sustainability assessment of renewable energy systems such as wind (on-shore), solar PV and fuel cell are presented in this paper. Solar PV, wind, and fuel cell energy systems are clean power systems, but the decision-making on the type of renewable energy system is very risky and difficult (different type of renewable energy systems and multiple decision criteria). Sustainability assessment is very important for the selection of the best renewable energy systems with respect to sustainability indicators (prioritizing sustainability indicators), for the development of sustainable energy, and for decision-making for the policy makers.

2. Renewable energy systems and multi-criteria decision-making model

2.1. Renewable energy systems

Four renewable power systems: polysilicon solar PV (A_1), onshore wind (A_2), phosphoric acid fuel cell PAFC (A_3) and solid oxide fuel cell (A_4) are selected in this study to assess their sustainability indicators. Solar PV and wind energy are also selected because solar PV and wind represent nearly 55% and 29% of newly installed renewable power capacity in 2017, respectively [30]. Several countries are successfully integrating increasingly larger shares of variable renewable power (solar PV and wind) into electricity systems. Fuel cell is chosen in this study for its high electrical efficiency. It can be combined with solar PV and wind turbines using hybrid power systems given the intermittent solar and wind resources. Solar PV power system converts solar radiation into electricity by using semiconductor materials (silicon). The solar panel is composed of solar cells that generate electrical power using solar energy. The efficiency of solar PV cells is about 13–16% for polysilicon and it can reach 20% with pure silicon. Wind turbine converts the kinetic energy of the wind to electricity via rotating blades, gearbox and generator. The power coefficient of the wind turbine is between 35 and 45%. Phosphoric acid fuel cell is a power system that converts the chemical energy of the fuel such as hydrogen into electricity. The system uses phosphoric acid electrolyte at low temperature (150–200 °C). The fuel cell consists of anode and cathode separated by electronically insulating electrolyte (phosphoric acid). Low efficiency (40%) is obtained with the PAFC fuel cell. The solid oxide fuel cell has better efficiency (50–60%) and operates at high temperature (600–1000 °C). Renewable energy systems are clean power systems used to generate electricity but the resource (material, area, energy, CO_2, and cost for the construction of the energy system) and the operational (capacity factor and system efficiency) parameters are different. These parameters should be included in the sustainability assessment of renewable energy systems.

2.2. Multi-criteria decision-making model - sustainability indicators and their sub-categories

Five sustainability indicators and fourteen sub-categories are selected for the sustainability analysis in this study (See Table 1). The resource indicator is related to the resources (material, energy, area …) used during the construction of renewable energy systems. The environment indicators are given by the greenhouse gas emissions (CO_2) during the construction and the use of energy systems. Economic indicators are related to the capital and fuel costs of the energy system and the delivered cost of energy. The social indicator is related to conditions impacting the well-being of individuals or communities (ensure access to affordable, reliable and sustainable energy for all). The technology indicator is related to the performance of energy systems such as system efficiency, capacity factor and lifetime of the system. Table 1 summarizes, in more details, the main sustainability indicators (criteria) and the sub-indices (sub-criteria) and their notations used in the present study.

3. Methodology – hybrid extended SWARA/ARAS COMPUTATIONAL method

In order to achieve the aim of this research, the evaluation of the selected renewable energy technologies has been done according to the fourteen criteria presented in the CES EduPack software from Granta Design [31] and classified by the authors into five groups of main sustainability indicators as presented in Table 1.

The evaluated technologies and their abbreviations which are used throughout the procedure of this research are:

A_1: Solar energy systems [poly-silicon]
A_2: Wind energy systems [land-based]
A_3: Phosphoric acid fuel cells
A_4: Solid oxide fuel cells.

An extended SWARA method was used to determine the weights of the evaluation criteria, while the evaluation process was done using ARAS method. The evaluation process required to put grades in the scale (1–5) as an indication of the performance of the different proposed alternatives. The performance of each technology was referenced to the global values provided by CES EduPack Software [31].

3.1. Classical Step-wise Weight Assessment Ratio Analysis (SWARA) method

In multi-attributes decision-making problems, the calculation of the weights of the evaluation criteria is a crucial component for the selection or ranking process. Different categories of criteria weighing approaches have been developed in the past: objective, subjective, and integrated approaches. The subjective approach has been used to represent the personal judgment of experts based on their experience and implicit knowledge, and it can therefore be described as a numerical representation of their experience [28]. However, the objective approach is based on mathematical programming models [32]. The integrated approach is a combination of both subjective and objective approaches [28,29].

The SWARA method is a new subjective criteria-weighing method with a wide application in various fields such as economics, management, industry, manufacturing, design and architecture, policy and environmental sustainability. What attracts attention to this method is that it is uncomplicated, straightforward and it involves a low number of comparisons in contrast to other weighing methods. In addition, another superiority of this method is that it can address the prioritizing process based on the current situation of policy, environment and economics [29,33–35].

The computational procedure of the classical model of SWARA method is described in detail in Appendix A [28,35].

3.2. Extended version of step-wise Weight Assessment Ratio Analysis (SWARA) method

Despite the wide usage of subjective weighing methods, especially SWARA method in different applications and its advantages, these methods, in some fields, lacked the certainty and rigorous judgment that differs from subjective and personal sense, especially in the areas that needs reliable, accurate and strict decision-making. In such cases, a slight difference in the criteria weight can highly affect the alternative performance and result in uncertain and unreliable ranking/selection. Therefore, to increase the accuracy rate and the reliability of SWARA method and minimize the subjective effect of personal judgment on the results, Hashemkhani et al. [29] applied an additional step to the classic SWARA methodology [29,36–40]. In this study, this extended SWARA method [29,33] will be utilized in ranking the selected renewable power systems, as will be described in the following section.

The procedure for the determination of weights by the extended

Table 1
Multi criteria decision making model - sustainability indicators (main criteria) and Their sub-criteria.

	Proposed criteria and sub-criteria	abbreviation	Definition
C_1	**Resource Indicator**	**RE**	
$C_{1\text{-}1}$	Area Intensity [m^2/kW]	AIN	The land area used by the power system per unit rated power (kW) of the system. To obtain the area per kW of actual delivered power capacity, divide the area intensity by the capacity factor (expressed as a fraction).
$C_{1\text{-}2}$	Material Intensity [kg/kW]	MIN	The quantities of materials (in kg) required to build a given power system per unit nominal power (kW). To calculate the material required per kW of actual delivered power, divide the material intensity by the capacity factor (expressed as a fraction).
$C_{1\text{-}3}$	Energy Intensity (construction) [MJ/kW]	EIN_C	The energy used to construct the power system, per unit rated power (kW) of the system. To obtain the build-energy per kW of actual delivered power, divide the energy intensity by the capacity factor (expressed as a fraction).
$C_{1\text{-}4}$	Energy Intensity (fuel) [MJ/kWh]	EIN_F	The energy (in MJ) that is consumed as fuel by the power system to generate each kWh of delivered energy.
C_2	**Environmental Indicator**	**EN**	
$C_{2\text{-}1}$	CO_2 Intensity (construction) [kg/kW]	CO_2 IN_C	The quantity of carbon dioxide, in kg, released to atmosphere during the construction of a given power system per unit of nominal power (kW_{nom}) of the system.
$C_{2\text{-}2}$	CO_2 Intensity (fuel) [kg/kWh]	CO_2 IN_F	The quantity of carbon dioxide, in kg, released to atmosphere because of the burning of hydrocarbons by the power system per kWh of delivered energy.
C_3	**Economic Indicator**	**EC**	
$C_{3\text{-}1}$	Capital Intensity (construction) [US$/kW]	CIN_C	The quantity of capital (money) used to construct the power system per unit rated power (kW_{nom}, for example) of the system. To obtain the cost per kW of actual delivered power, divide the capital intensity by the capacity factor (expressed as a fraction).
$C_{3\text{-}2}$	Capital Intensity (fuel) [US$/kWh]	CIN_F	The cost of the fuel used in the system per kWh of delivered energy. This is based on input/output figures from plants and scaled to be a nominal value.
$C_{3\text{-}3}$	Delivered cost [US$/kWh]	DLC	The cost of generating one kWh of electrical energy for a given power system.
C_4	**Social Indicator**	**SO**	
$C_{4\text{-}1}$	Current installed capacity [GW]	CIC	The total global rated capacity of power systems of this type.
$C_{4\text{-}2}$	Growth rate [% fraction/year]	GRR	The rate at which installed capacity currently grows each year, expressed as a percentage.
C_5	**Technology Indicator**	**TE**	
$C_{5\text{-}1}$	Capacity factor [%]	CPF	The fraction of time, expressed as a percentage that a power system operates at its rated power. This takes into account time when a system would be unavailable, or generating less power than it potentially could, due to maintenance or because the natural resource it uses is unavailable.
$C_{5\text{-}2}$	System efficiency [%]	EFF	The efficiency, expressed as a percentage, with which the fuel or resource is converted into electricity.
$C_{5\text{-}3}$	Lifetime [years]	LFT	The expected time (in years) that the power system will remain fully operational.

SWARA method is stated in the steps below:

Step 1: **Ranking the proposed attributes based on the significance level**

Each criterion j and sub-criterion i, (if there are groups of criteria), is given a rank value with respect to other counterparts by each member in the group of experts using his/her implicit knowledge and experience. They rank the criteria based on their expected significance.

Then, the average attribute rank value is calculated using the following Equation:

$$\bar{t}_j = \frac{\sum_{k=1}^{r} t_{jk}}{r} \tag{1}$$

Next, the final attributes ranks $\boldsymbol{t_{jf}}$ are stated as exact numbers based on the average attribute rank values in an ascending order (e.g. the smallest average attribute rank value is given the first rank and the highest is given the last rank).

(Note that when applying this Equation for the sub-criteria in this paper, $\bar{t}_j = \bar{t}_i$, $t_{jk} = t_{ik}$, and $\boldsymbol{t_{j,f} = t_{i,f}}$, where $\bar{t}_i$ is the average attribute rank value of the ***i***th sub-criterion, t_{ik} is the rank of the i^{th} sub-criterion by the k^{th} expert, and $\boldsymbol{t_{i,f}}$ is the final attribute rank of the sub-criterion).

Step 2: *Calculating the comparative importance* $\boldsymbol{s_j}$ and the reliability of experts' judgement

In this step, the extension of classical SWARA added by Hashemkhani et al. [29] and proposed initially by Kendall [37] to calculate attribute weights by experts and test the reliability of experts' judgments is presented [29,37].

This step consists of 4 sub-steps as follows:

$$\frac{\bar{t}_j}{\sum_{j=1}^{n} t_{j,f}} \tag{2}$$

***Step 2-1*:** Determination of the value of the attribute importance compared to other counterparts of criteria. In classical SWARA method, Keršuliene [28] called this value "the comparative importance of average value "s_j" ", and it was obtained by setting rough numbers by experts to express the relative importance of one criterion with respect to the next one. In this research, to increase the reliability of the applied method and make the obtained results more reliable (away from subjective judgment), this value was calculated using Equation (2) [29]:

(Note that when applying this Equation for the sub-criteria in this paper, $\bar{t}_j = \bar{t}_i$, and $\sum_{j=1}^{n} t_{j,f} = \sum_{i=1}^{b} t_{i,f}$ where; $\bar{t}_i$ is the average attribute rank value for the i^{th} sub-criterion, b is the number of the sub-criteria which is = 14 in this study, and $\sum_{i=1}^{b} t_{i,f}$ is the summation of the final ranks of all sub-criteria).

$$\sigma^2 = \frac{1}{r-1} \sum_{k=1}^{r} \left(t_{jk} - \bar{t}_j\right)^2 \tag{3}$$

$$\beta_j = \frac{\sigma}{\bar{t}_j} \tag{4}$$

Step 2-2: In this step, some statistical processes are applied to calculate how far the experts' judgments are away from each other. This is achieved by calculating the dispersion of experts' ranking σ^2 using Equation (3), and the variation β_j of the obtained results using Equation (4).

(Note that when applying these Equations for the sub-criteria in this paper, $t_{jk} = t_{ik}$, and $\bar{t}_j = \bar{t}_i$ where; t_{ik} is the ranking of the ***i***th sub-criterion by the k^{th} expert, and $\bar{t}_i$ is the average attribute rank value for the i^{th} sub-criterion).

$$W = \frac{12S}{r^2(n^3 - n) - r\sum_{k=1}^{r} T_k} W \in [0; 1] \tag{5}$$

Step 2–3 In this step another statistical process is applied to compute how close the experts' judgments are from each other. This is achieved by calculating the coefficient of concordance (agreement) of the experts' views. The reliability of the data is expressed by this coefficient W. The coefficient of concordance can be calculated from Equation (5).

S is the total square deviation of the rankings of each attribute and can be calculated from Equation (6) below:

$$S = \sum_{j=1}^{n} \left[\sum_{k=1}^{r} t_{jk} - \frac{1}{n} \sum_{j=1}^{n} \sum_{k=1}^{r} t_{jk} \right]^2 \tag{6}$$

(Note that when applying these Equations for the sub-criteria in this paper, $T_k = 0$, $n = b$. b is the number of sub-criteria which is = 14 in this study, and $\sum_{k=1}^{r} t_{jk} = \sum_{k=1}^{r} t_{ik}$. $\sum_{k=1}^{r} t_{ik}$ is the summation of the rankings by all experts for each i^{th} sub-criterion).

Step 2–4 This step is applied because the obtained value of W is stochastic [29,37–40]. Therefore, an extra statistical parameter has to be calculated which is the significance $\chi^2_{\alpha,\nu}$ of the coefficient of concordance at a certain level of significance α, and degrees of freedom ν [40].

[29,37–39], and [40] showed that when the number of the evaluation criteria is greater than 7, then $\chi^2_{\alpha,\nu}$ has a distribution with degrees of freedom of $\nu = n$-1, where n is the number of the evaluation criteria.

The significance of the concordance coefficient is calculated as follows:

$$\chi^2_{\alpha,\nu} = W.\, r; (n-1) = \frac{12S}{rn(n+1) - \frac{1}{n-1}\sum_{k=1}^{r} T_k} \tag{7}$$

(Note that in this study, this value has its significance in the experts' judgments on the sub-criteria since they are 14 > 7, and in this case $n = b$ where b is the number of sub-criteria. Also, note that $T_k = 0$).

$\chi^2_{\alpha,\nu}$ is used to test the significance of the concordance coefficient according to the following criterion [29,37–41]:

If the calculated value of $\chi^2_{\alpha,\nu}$ at a certain pre-selected level of significance (e.g. $\alpha = 0.05$), corresponds to error probability in experts' judgments of 5% according to Ref. [42] is larger than the critical tabular value χ^2_{tbl} in the statistical tables for biological, agricultural and medical research [41], then the hypothesis about the agreement of independent experts' views and judgments is accepted and group opinion is established. In this case, it can be said that the significance of the concordance coefficient exists in α level. However, if $\chi^2_{\alpha,\nu} < \chi^2_{tbl}$, then the experts' opinion is not in agreement, which implies that they differ substantially and the hypothesis on the rank's correlation cannot be accepted.

Next, the following three steps are similar to the last three steps of the classical SWARA method to obtain the final attribute weight.

Step 3: The coefficient k_j is calculated as follows;

$$k_j = \begin{cases} 1 & j = 1 \\ s_j + 1 & j > 1 \end{cases}$$

Step 4: The recalculated weight q_j is calculated as follows;

$$q_j = \begin{cases} 1 & j = 1 \\ \dfrac{q_{j-1}}{k_j} & j > 1 \end{cases}$$

Step 5: The relative weights w_j of the evaluation criteria are determined as follows;

$$w_j = \frac{q_j}{\sum_{m=1}^{n} q_m}$$

(Note that when applying these Equations for the sub-criteria in this paper, $n = b$. b is the number of the sub-criteria which is = 14 in this study, and $j = i$, where i denotes the i^{th} sub-criterion).

3.3. Additive ratio assessment method (ARAS)

The additive ratio assessment method (ARAS) is a newly developed multi-criteria decision-making (MCDM) method proposed by Zavadskas & Turskis [42]. It found a wide application in different fields such as: personnel selection [43], ranking of companies according to the indicators of corporate social responsibility [44], the selection of the chief accountant [45], the ranking of financial institutions based on trust in online banking [46], and in the assessment of sustainable building [47].

Its wide application and fast growing are consequences of its simple, direct, easy and straightforward steps, which yields reasonable, acceptable and relatively accurate results in ranking/selecting different proposed alternatives based on their performance with respect to selected weighted evaluation criteria. There are many elaborations on this method in last few years and several publications were found in different areas, such as the grey additive ratio assessment (ARAS-G) method [48] and its extension for decision-making problems with interval-valued triangular fuzzy numbers [49]. This is a proof of the effectiveness and usefulness of the ARAS method. According to Refs. [42–44], the ARAS method can be used to solve MCDM problems by applying the following steps:

Step 1: Creating the decision matrix and determining the optimal performance rating for each criterion

In order to create the decision matrix, each evaluator in the decision makers group has to give grades as an indication of the relative performance of the a^{th} alternative with respect to the j^{th} criterion. These grades are selected to be in a specific scale of a descending or an ascending order (e.g. a scale 1–5). The overall evaluation grade of each alternative by the group of experts is calculated as the geometric mean grade with respect to each j^{th} criterion as follows:

$$x_{aj} = \left(\prod_{k=1}^{r} x_{aj}^{k}\right)^{\frac{1}{r}} \tag{8}$$

The optimal performance rating is the one which performs best among all alternatives with respect to a specific criterion, thus;

$$x_{0j} = max_a \, x_{aj} \tag{9}$$

where x_{0j} is the optimal performance rating with respect to the j^{th} criterion, (e.g. the highest score in a benefit criterion).

(Note that when applying these Equations for the sub-criteria in this paper, $j = i$, $n = b$. i is an indication of the sub-criteria, and b is the number of sub-criteria which is = 14 in this study).

Step 2: Calculating the Normalized Decision-Making Matrix

After creating the decision matrix, normalization to the performance ratings must be done to compare between alternatives with respect to different evaluation criteria. The normalized performance ratings can be calculated using Equation (10) as follows:

$$x_{aj,N} = \frac{x_{aj}}{\sum_{a=1}^{m} x_{aj}} \tag{10}$$

(Note that when applying these Equations for the sub-criteria in this paper, $j = i$. i is an indication of the sub-criteria).

Step 3: Calculating the weighted normalized decision-making matrix

In order to calculate the weighted normalized decision-making matrix, the weights of the evaluation criteria must be calculated using one of the criteria weighing methods such as the Step-wise Weight Assessment Ratio Analysis (SWARA) method.

According to Refs. [32,44], in case of the presence of different categories of criteria (e.g. main criteria and sub-criteria), the resultant weight of the sub-criteria that represents the weight of both the main criteria and its sub-criteria must be calculated (the integrated weight), and it is the one which can be used in the ARAS method.

The resultant weight of the sub-criteria can be calculated using the following Equation:

$$w_{ij}^{r} = \frac{w_j \, w_{ij}}{\sum_{i,j} wj \, w_{ij}} \tag{11}$$

The normalized weighted decision matrix is calculated as follows:

$$\upsilon_{aj} = w_{ij}^{r} \times x_{aj,N} \tag{12}$$

Step 4: Calculating the overall performance index for each alternative

The overall performance index of the alternative S_a is an indication of the overall evaluated performance of the a^{th} alternative with respect to all evaluation criteria, and can be calculated as follows:

$$S_a = \sum_{j=1}^{n} \upsilon_{aj} \tag{13}$$

(Note that when applying this Equation in this paper, $n = b = 14$, where b is the number of the evaluation criteria).

Step 5: Calculating the degree of utility for each alternative

Q_a represents the degree of utility of each alternative, which is the relative performances of the considered alternatives/candidates in relation to the best-ranked alternative/candidate. The proposed candidates are ranked in an ascending order Q_a, (higher values of Q_a means higher priority or rank). The alternative with the largest value of Q_a is the best (ranked first). Q_a can be calculated as follows:

$$Q_a = \frac{S_a}{S_0} \tag{14}$$

Q_a with a value of 1 is the optimal alternative.

Step 6: Ranking the evaluated alternatives/selecting the most efficient one

The considered alternatives are ranked in an ascending order Q_a, i.e., the alternatives with the higher values of Q_a have a higher priority (rank) and the alternative with the largest value of Q_a is the best-placed one.

4. Results and discussions

The results of the assessment of sustainability indicators for solar PV, wind, phosphoric acid, and solid oxide fuel cells power systems are presented in this section. The results are obtained with the multi-criteria decision-making (MCDM) model and hybrid SWARA/ARAS method using the five main sustainability indicators (resource, environment, economy, society and technology) and fourteen sub-categories. Using the steps of the extended SWARA/ARAS method explained in the methodology section, the following results were obtained. The first results are related to the application of the extended SWARA method. The ranking of the proposed attributes based on the significance level is determined. The results include the rankings of the main sustainability indicators and their sub-indices or sub-categories by the three energy experts. The results of this assessment for the main sustainability indicators and subcategories are presented in Figs. 2 and 3, respectively. The results presented in these figures are based on the collected data from the three energy experts shown in Tables A 2.1 and A 2.2 (Appendix A). Then, the average attribute rank values were calculated using Equation (1). The average attribute rank values of the main sustainability criteria and the sub-criteria are presented in the second raw of Tables 2 and 3, respectively. The final ranks of the main criteria $\boldsymbol{t}_{j,f}$, and the sub-criteria $\boldsymbol{t}_{i,f}$ are presented in Figs. 4 and 5, respectively. The C_2 criteria related to the environment was ranked first followed by the C_3 (economic), C_5 (technology), C_4 (social) and C_1 (resources). For the sub-categories, the CO_2 emissions during the use of the power system were ranked first and the area intensity (m^2/kWh) was ranked last from the fourteen sub-criteria. The ranking

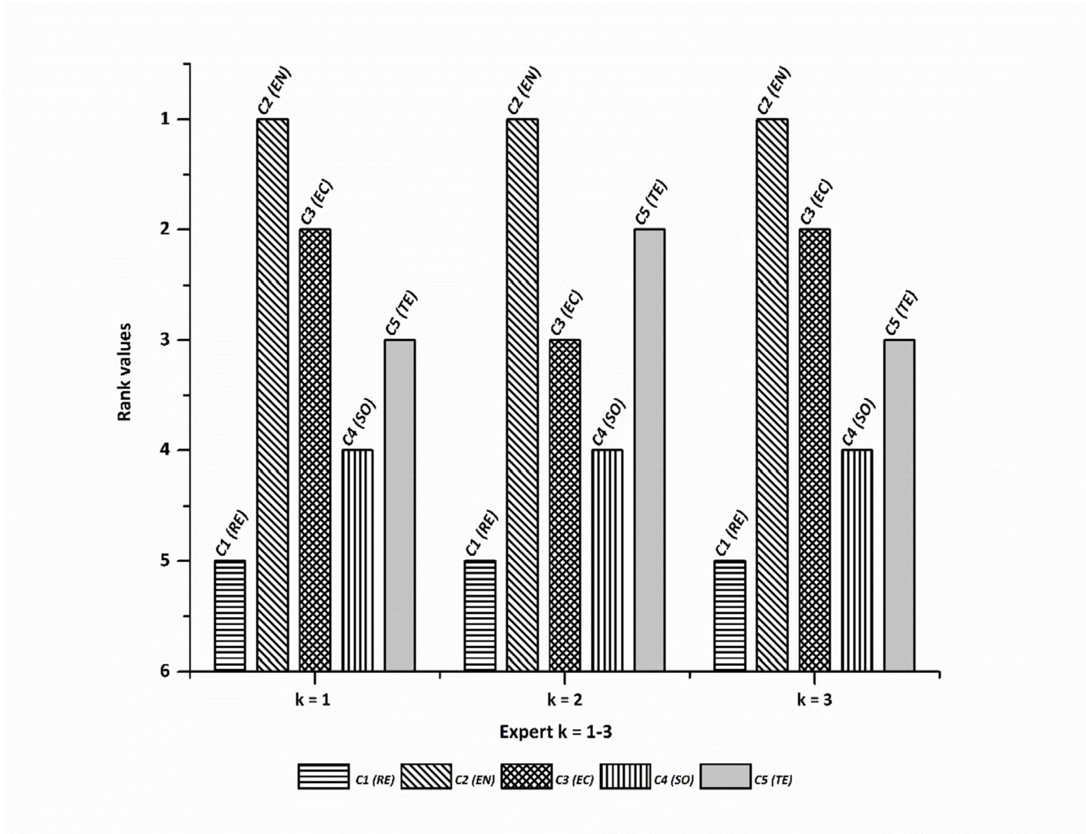

Fig. 2. Ranking of the main sustainability indicators based on the significance level from the three experts.

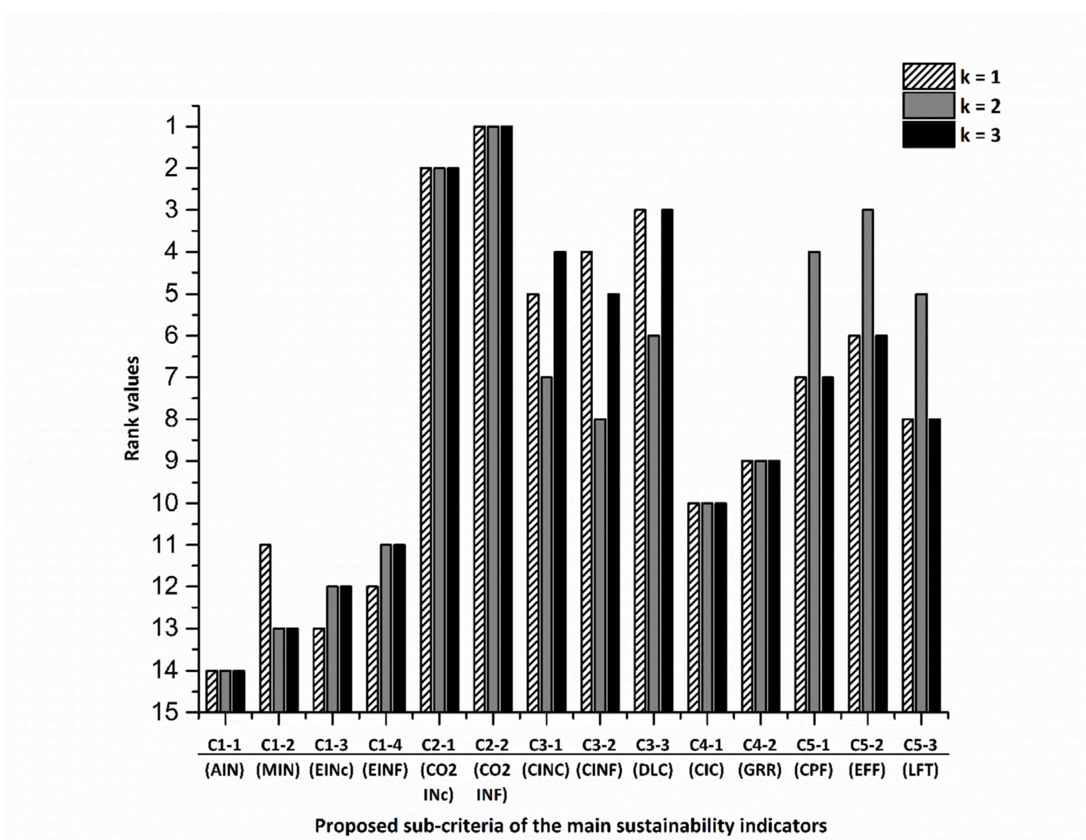

Fig. 3. Ranking of the sub-criteria of the main sustainability indicators based on the significance level from the three experts.

Table 2
Final attributes ranks for the main sustainability criteria.

Process of computation	Proposed criteria				
	C_1 (RE)	C_2 (EN)	C_3 (EC)	C_4 (SO)	C_5 (TE)
Sum of the ranks $\sum_{k=1}^{r=3} t_{jk}$	15	3	7	12	8
Average attribute rank value $\bar{t}_j = \frac{\sum_{k=1}^{r=3} t_{jk}}{r}$	5	1	2.33	4	2.67
Attribute final rank ($t_{j,f}$)	5	1	2	4	3

procedure considers that the sustainability indicators are not of the same importance and it was done by three energy experts based on their experience and implicit knowledge according to the current state of economy, environment, society, resources, and technologies. The second step for the extended SWARA method was to calculate the comparative importance s_j and the reliability of experts' judgement. The values of the attribute importance compared to other counterparts of criteria using Equation (2) was determined and the results are presented in Table 4 for both the main sustainability criteria and their sub-categories. The dispersion of experts ranking σ^2 (see Equation (3)), and the variation β_j of the obtained results (see Equation (4)) were then determined. The results of these two steps, for the main sustainability criteria and sub-criteria are presented in Tables 5 and 6, respectively. The coefficient of concordance $\boldsymbol{W}$ using Equations (5) and (6) are then calculated using the following procedure:

Calculating $\boldsymbol{W}$ of the rankings of the main criteria;

Let $V = \frac{1}{n}\sum_{j=1}^{n}\sum_{k=1}^{r} t_{jk}$, then;

$$V = \frac{1}{5}\sum_{j=1}^{5}\sum_{k=1}^{r=3} t_{jk} = \frac{1}{5}[15+3+7+12+8] = 9$$

$$\boldsymbol{S} = \sum_{j=1}^{5}\left[\sum_{k=1}^{r=3} t_{jk} - 9\right]^2 = (15-9)^2 + (3-9)^2 + (7-9)^2 + (12-9)^2 + (8-9)^2 = 86$$

$$\text{then, } \boldsymbol{W} = \frac{12*86}{3^2\left(5^3-5\right)} = 0.96$$

Calculating $\boldsymbol{W}$ of the rankings of the sub-criteria;

Let $V = \frac{1}{b}\sum_{i=1}^{b}\sum_{k=1}^{r} t_{ik}$, then;

$$V = \frac{1}{14}\sum_{i=1}^{14}\sum_{k=1}^{r=3} t_{ik} = \frac{1}{14}[42+37+37+34+6+3+16+17+12+30+27+18+15+21] = 22.5$$

$$\boldsymbol{S} = \sum_{i=1}^{14}\left[\sum_{k=1}^{r=3} t_{ik} - 22.5\right]^2 = (42-22.5)^2 + (37-37)^2 + (37-22.5)^2 + (34-22.5)^2 + (6-22.5)^2 + (3-22.5)^2 + (16-22.5)^2 + (17-22.5)^2 + (12-22.5)^2 + (30-22.5)^2 + (27-22.5)^2 + (18-22.5)^2 + (15-22.5)^2 + (21-22.5)^2 = 1923.5$$

then, $\boldsymbol{W} = \frac{12*1923.5}{3^2(14^3-14)} = \mathbf{0.94}$.

The significance of the concordance coefficient $\chi^2_{\alpha,\nu}$ is then calculated using Equation (7). By applying Equation (7) to the sub-criteria yields:

$$\chi^2_{0.05,13} = 0.94 \times 3 \times (14-1) = \frac{12 \times 1923.5}{3 \times 14\,(14+1)} = 36.638$$

To compare this value of $\chi^2_{\alpha,\nu}$ with the critical tabular value of χ^2_{tbl} at the same selected level of significance of $\alpha = 0.05$ and degrees of freedom of $\nu = 13$ (b - 1 = 14–1), Table 4 in the statistical tables for the biological, agricultural and medical research of Fisher and Yates [41] was used. The value reported in Table 4 [41] was $\chi^2_{tbl} = \mathbf{22.362}$.

It is clear that $\chi^2_{0.05,13} = 36.638 > \chi^2_{tbl} = 22.362$, thus the assumption that the coefficient of the concordance of experts' views is significant is accepted, and experts' rankings are in agreement. The final results of the application of the extended SWARA method to obtain the final attribute weights of the main criteria and the sub-criteria are presented in Tables 7 and 8, and in Figs. 6 and 7, respectively. The results of the main sustainability criteria show that the weights of the environmental, economic, technological, social, and resources criteria are respectively 27.7%, 23.9%, 20.3%, 16% and 12%. The environmental sustainability criterion has the highest weight and the resources have the lowest weight.

The second part of this study is to combine the ARAS method with the extended SWARA method (hybrid SWARA/ARAS) for the assessment and development of sustainability indicators for four renewable power systems. The first step for the ARAS method was to create a decision matrix and to determine the optimal performance rating for each criterion. The decision matrix was created by evaluating the selected alternatives from the three experts by

Table 3
Final attributes ranks for the sustainability sub-criteria.

Process of computation	Proposed criteria													
	$C_{1\text{-}1}$ (AIN)	$C_{1\text{-}2}$ (MIN)	$C_{1\text{-}3}$ (EIN_C)	$C_{1\text{-}4}$ (EIN_F)	$C_{2\text{-}1}$ (CO_2 IN_C)	$C_{2\text{-}2}$ (CO_2 IN_F)	$C_{3\text{-}1}$ (CIN_C)	$C_{3\text{-}2}$ (CIN_F)	$C_{3\text{-}3}$ (DLC)	$C_{4\text{-}1}$ (CIC)	$C_{4\text{-}2}$ (GRR)	$C_{5\text{-}1}$ (CPF)	$C_{5\text{-}2}$ (EFF)	$C_{5\text{-}3}$ (LFT)
Sum of the ranks $\sum_{k=1}^{r=3} t_{ik}$	42	37	37	34	6	3	16	17	12	30	27	18	15	21
Average attribute rank value $\bar{t}_i = \frac{\sum_{k=1}^{r=3} t_{ik}}{r}$	14	12.33	12.33	11.33	2	1	5.33	5.67	4	10	9	6	5	7
Attribute final rank ($t_{i,f}$)	13	12	12	11	2	1	5	6	3	10	9	7	4	8

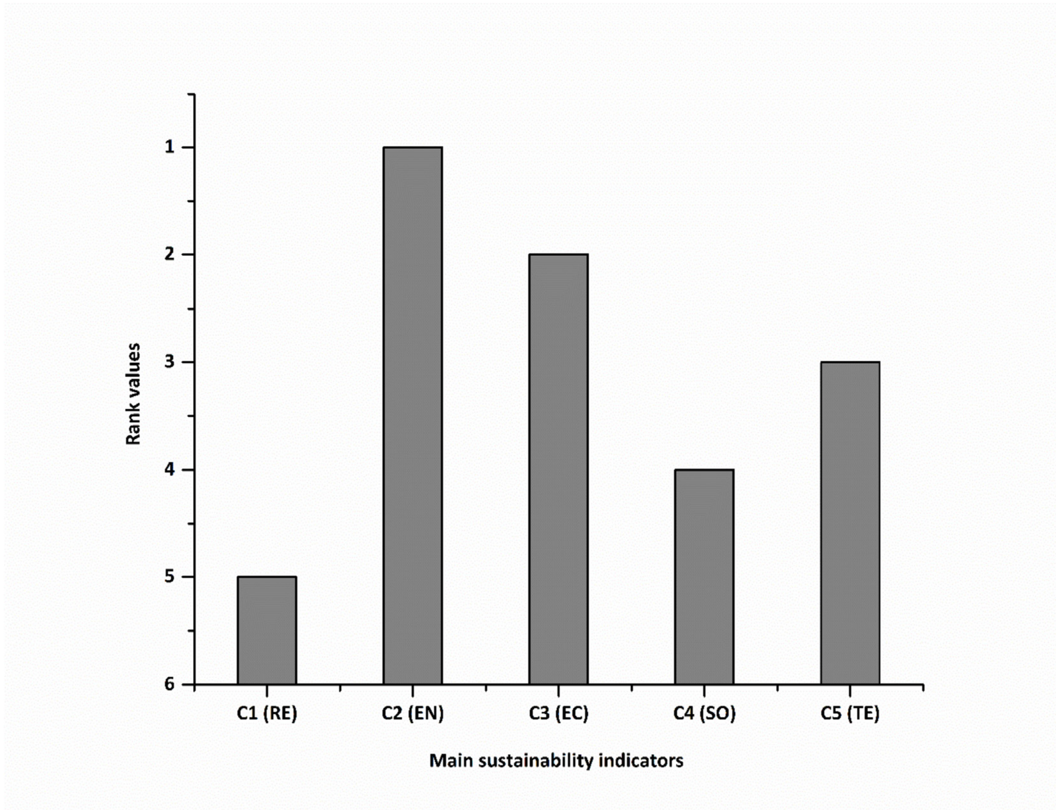

Fig. 4. Final ranks of the main sustainability indicators.

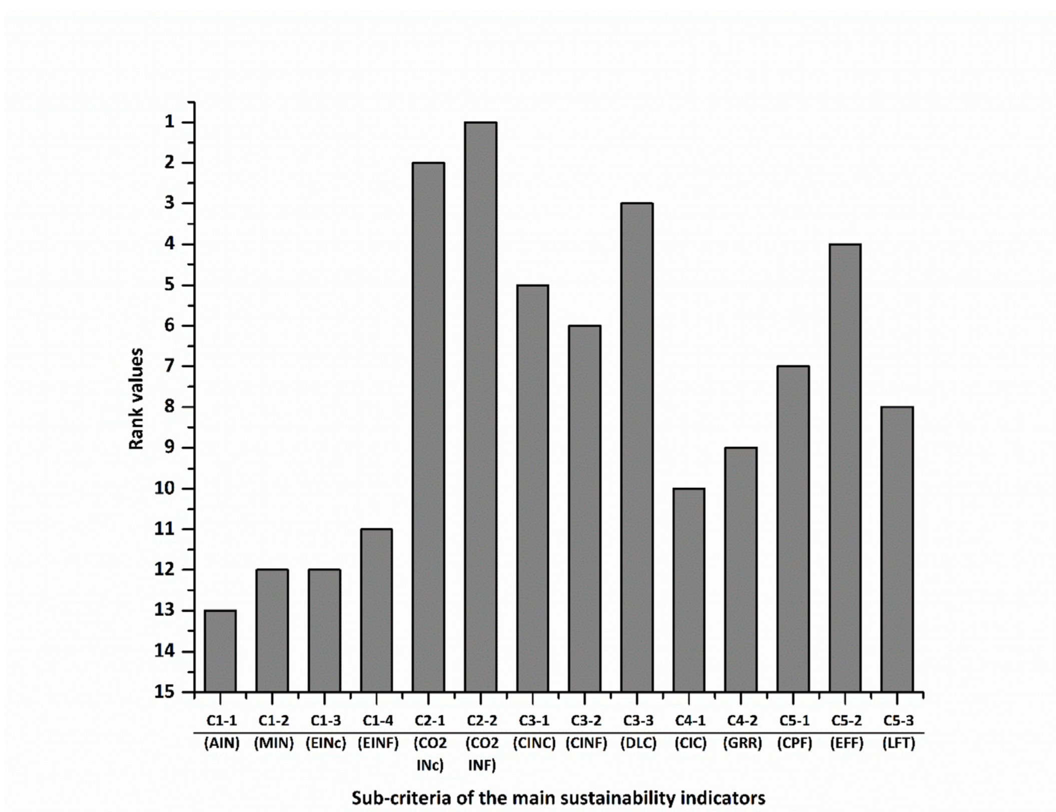

Fig. 5. Final ranks of the sub-criteria of the main sustainability indicators.

Table 4
Attributes' comparative importance s_j.

Final rank	Main criteria	Comparative importance of average value s_j	Final rank	Sub-criteria	Comparative importance of average value s_j
1	C_2 (EN)	0.067	1	C_{2-2} (CO_2 IN_F)	0.010
2	C_3 (EC)	0.156	2	C_{2-1} (CO_2 IN_C)	0.019
3	C_5 (TE)	0.178	3	C_{3-3} (DLC)	0.039
4	C_4 (SO)	0.267	4	C_{5-2} (EFF)	0.049
5	C_1 (RE)	0.333	5	C_{3-1} (CIN_C)	0.052
			6	C_{3-2} (CIN_F)	0.055
			7	C_{5-1} (CPF)	0.058
			8	C_{5-3} (LFT)	0.068
			9	C_{4-2} (GRR)	0.087
			10	C_{4-1} (CIC)	0.097
			11	C_{1-4} (EIN_F)	0.110
			12	C_{1-3} (EIN_C)	0.120
			13	C_{1-2} (MIN)	0.120
			14	C_{1-1} (AIN)	0.136

Table 5
Dispersion of expert ranking and the variation of the obtained values for the main criteria. $\mathbf{C_{1-1}}$ (AIN) $\mathbf{C_{1-2}}$ (MIN) $\mathbf{C_{1-3}}$ (EIN_C) $\mathbf{C_{1-4}}$ (EIN_F) $\mathbf{C_{2-1}}$ (CO_2 IN_C) $\mathbf{C_{2-2}}$ (CO_2 IN_F) $\mathbf{C_{3-1}}$ (CIN_C) $\mathbf{C_{3-2}}$ (CIN_F) $\mathbf{C_{3-3}}$ (DLC) $\mathbf{C_{4-1}}$ (CIC) $\mathbf{C_{4-2}}$ (GRR) $\mathbf{C_{5-1}}$ (CPF) $\mathbf{C_{5-2}}$ (EFF) $\mathbf{C_{5-3}}$ (LFT).

Process of computation	Main criteria				
	C_1 (RE)	C_2 (EN)	C_3 (EC)	C_4 (SO)	C_5 (TE)
$\sum_{k=1}^{r}(t_{jk} - \bar{t}_j)^2$	0	0	0.67	0	0.67
$\sigma^2 = \frac{1}{r-1}\sum_{k=1}^{r}(t_{jk} - \bar{t}_j)^2$	0	0	0.33	0	0.33
$\beta_j = \frac{\sigma}{\bar{t}_j}$	0	0	0.25	0	0.22

putting grades in a scale of (1–5) according to the ratings presented in Table 9. The grades were used based on the performance of the alternatives which is referenced to CES EduPack from Granta Design and summarized in Table 10. The experts' evaluation grades are presented in Tables A 3.1, A.3.2, and A 3.3 (see Appendix A), and the average grades of the alternatives obtained using Equation (8) are presented in Table 11. After creating the decision matrix, a normalization of the performance ratings is performed to compare between alternatives with respect to different evaluation criteria. The normalized performance ratings are calculated using Equation (10) and the results are reported in Table 12. The next step is to determine the weighted normalized decision-making matrix and the overall performance index for each alternative. The resultant weight of the sub-criteria that represents the weight of both the main criteria and its sub-criteria must be calculated based on the ARAS integrated weight using Equation (11). The results for the weights of the sub-criteria are shown in Table 13. The highest weight 13.29% for the sub-criteria is C_{2-2} which represents the quantity of carbon dioxide CO_2 released to the atmosphere due to hydrocarbon fuel combustion normalized by the delivered energy (kg CO_2/kWh). The lowest weight 2.22% for the sub-categories is C_{1-1} which represents the area per unit rated power (m^2/kW) of the system. The weighted normalized decision-making matrix and overall performance index of each alternative are then calculated using Equations (12) and (13) and the results are presented in Table 14. At the end, the degree of utility for each alternative, the ranking of the evaluated alternatives and the selection of the most efficient one were determined. Table 15 and Fig. 8 present the final results of the process of ranking the proposed renewable technologies using the extended SWARA-ARAS method. The column named Q_a represents the degree of utility of each alternative, which is the relative performance of the considered alternatives/candidates in relation to the best-ranked alternative/candidate. The considered alternatives are ranked in an ascending order Q_a, i.e., the alternatives with the higher values of Q_a have a higher priority (rank) and the alternative with the largest value of Q_a is the best

Table 6
Dispersion of expert ranking and the variation of the obtained values for the sub-criteria.

	$\mathbf{C_{1-1}}$ (AIN)	$\mathbf{C_{1-2}}$ (MIN)	$\mathbf{C_{1-3}}$ (EIN_C)	$\mathbf{C_{1-4}}$ (EIN_F)	$\mathbf{C_{2-1}}$ (CO_2 IN_C)	$\mathbf{C_{2-2}}$ (CO_2 IN_F)	$\mathbf{C_{3-1}}$ (CIN_C)	$\mathbf{C_{3-2}}$ (CIN_F)	$\mathbf{C_{3-3}}$ (DLC)	$\mathbf{C_{4-1}}$ (CIC)	$\mathbf{C_{4-2}}$ (GRR)	$\mathbf{C_{5-1}}$ (CPF)	$\mathbf{C_{5-2}}$ (EFF)	$\mathbf{C_{5-3}}$ (LFT)
$\sum_{k=1}^{r}(t_{jk} - \bar{t}_j)^2$	0	2.67	0.67	0.67	0	0	4.67	8.67	6	0	0	6	6	6
$\sigma^2 = \frac{1}{r-1}\sum_{k=1}^{r}(t_{jk} - \bar{t}_j)^2$	0	1.33	0.33	0.33	0	0	2.33	4.33	3	0	0	3	3	3
$\beta_j = \frac{\sigma}{\bar{t}_j}$	0	0.0936	0.0468	0.0509	0	0	0.286	0.367	0.433	0	0	0.289	0.346	0.247

Table 7
Final results of extended SWARA method in calculating the weights of the main criteria.

	Main criteria	Comparative importance of average value s_j	Coefficient $k_j = s_j + 1$	Recalculated weight [$q_j = \frac{q_{j-1}}{k_j}$]	Weight $w_j = \frac{q_j}{\sum q_j}$
1	C_2 (EN)		1	1	0.277
2	C_3 (EC)	0.156	1.156	0.865	0.239
3	C_5 (TE)	0.178	1.178	0.735	0.203
4	C_4 (SO)	0.267	1.267	0.580	0.160
5	C_1 (RE)	0.333	1.333	0.435	0.120
			Sum	3.615	1.000

Table 8
Final results of extended SWARA method in calculating the weights of the sub-criteria.

	Sub-criteria	Comparative importance of average value s_j	Coefficient $k_j = s_j + 1$	Recalculated weight $[q_j = \frac{q_{j-1}}{k_j}]$	Weight $w_j = \frac{q_j}{\sum q_j}$
1	$C_{2\text{-}2}$ (CO_2 IN_F)		1	1	0.099
2	$C_{2\text{-}1}$ (CO_2 IN_C)	0.019	1.019	0.981	0.097
3	$C_{3\text{-}3}$ (DLC)	0.039	1.039	0.944	0.094
4	$C_{5\text{-}2}$ (EFF)	0.049	1.049	0.901	0.089
5	$C_{3\text{-}1}$ (CIN_C)	0.052	1.052	0.856	0.085
6	$C_{3\text{-}2}$ (CIN_F)	0.055	1.055	0.812	0.081
7	$C_{5\text{-}1}$ (CPF)	0.058	1.058	0.767	0.076
8	$C_{5\text{-}3}$ (LFT)	0.068	1.068	0.718	0.071
9	$C_{4\text{-}2}$ (GRR)	0.087	1.087	0.660	0.066
10	$C_{4\text{-}1}$ (CIC)	0.097	1.097	0.602	0.060
11	$C_{1\text{-}4}$ (EIN_F)	0.110	1.110	0.542	0.054
12	$C_{1\text{-}3}$ (EIN_C)	0.120	1.120	0.484	0.048
13	$C_{1\text{-}2}$ (MIN)	0.120	1.120	0.433	0.043
14	$C_{1\text{-}1}$ (AIN)	0.136	1.136	0.381	0.038
			Sum	10.081	1.000

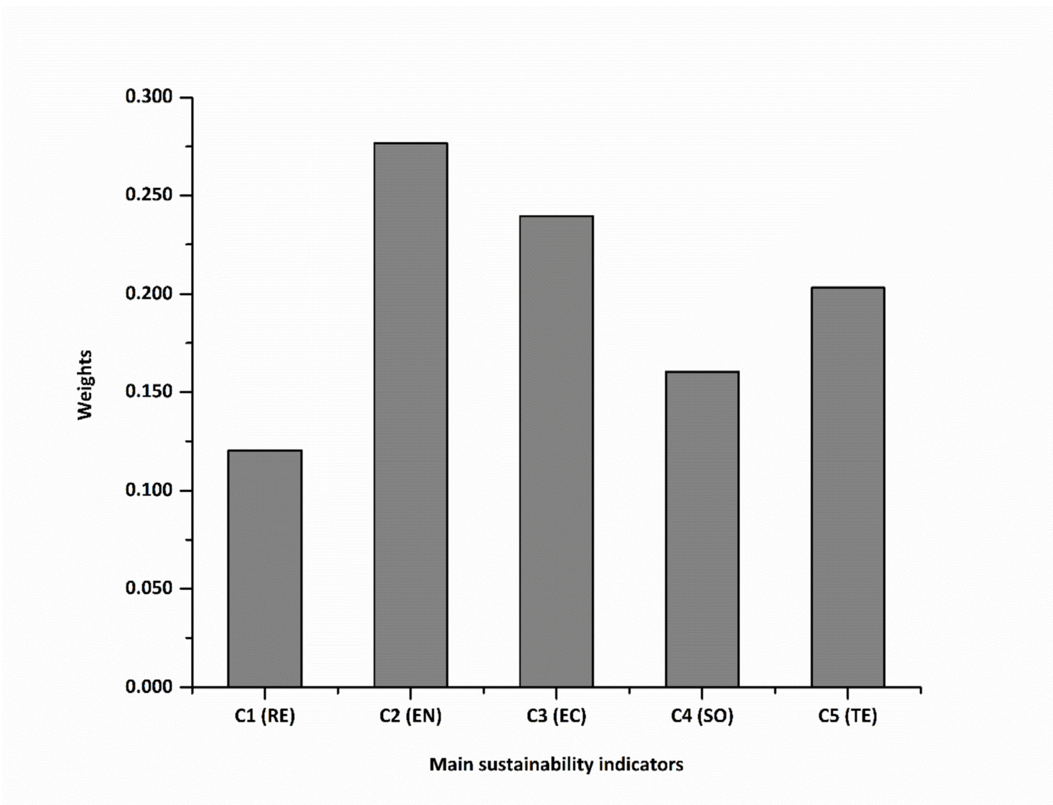

Fig. 6. Final weights of the main sustainability indicators.

renewable energy technology. In the present study, the land-based wind energy systems ranked as the first candidate in the sustainability assessment among the selected renewable power technologies. This is followed by solid oxide fuel cell, phosphoric acid fuel cell, and polysilicon solar energy systems, ranking last.

1. Wind energy systems [Land-based].
2. Solid oxide fuel cells.
3. Phosphoric acid fuel cells.
4. Solar energy systems [poly-silicon]

The multi-criteria decision-making (MCDM) model integrated with the hybrid SWARA/ARAS method is a useful methodology for sustainability assessment of renewable energy systems, sustainable energy development and for decision-making for policy makers. According to the variations in the level of importance of sustainability indicators, wind energy systems have no greenhouse gas emissions during operation and construction, so their contribution to global warming is negligible. Also, they have a high capacity factor and lifetime. These important properties of wind energy systems will compensate for their large land areas consumption, high material intensity for their construction, and the social issues associated with their noisy operation. Solar energy systems suffer from their low electrical efficiency, unsustainable energy storage

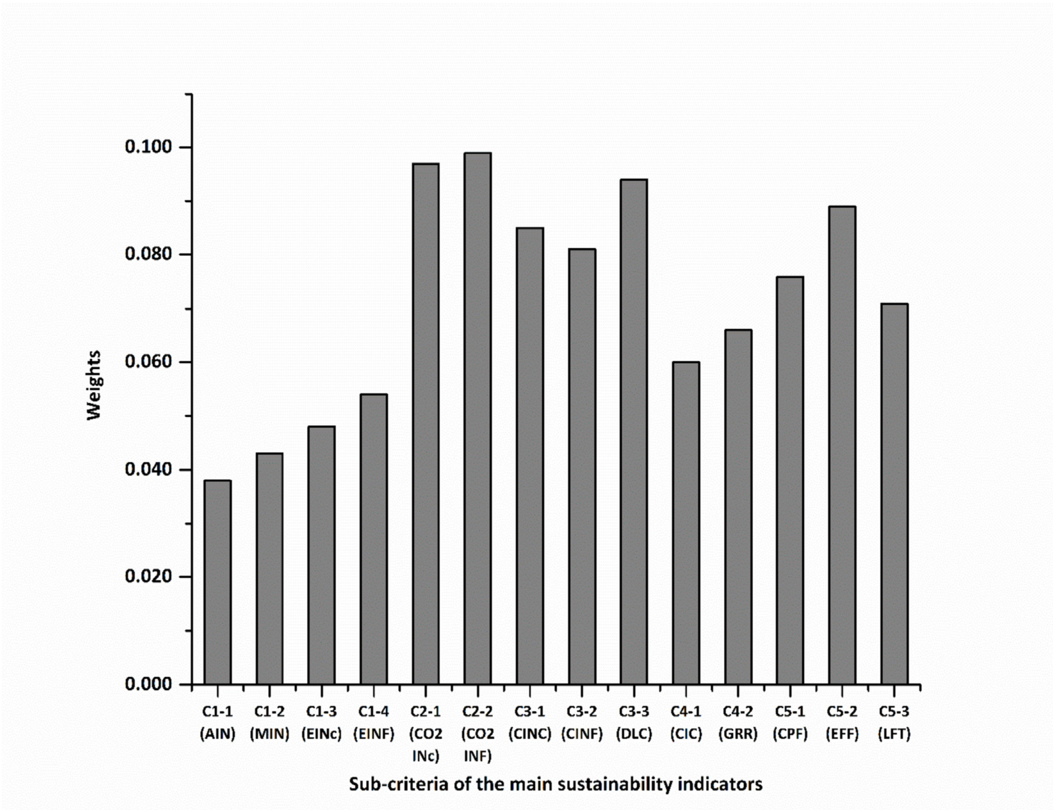

Fig. 7. Final weights of the sub-criteria of the main sustainability indicators.

Table 9
Evaluation rates.

Grade	Rate
5	Excellent
4	Very good
3	Good
2	Fair
1	Poor

systems needed for their intermittency, and the very high material intensity needed for their construction. Fuel cells are a developing technology that was able to promote its market in a short period of time due to its high electrical efficiency. Solid oxides fuel cell (SOFC) running with natural gas or propane as fuel are the most efficient fuel cells for electricity generation with low emissions (the carbon monoxide in exhaust gases is converted to CO_2 at high operating temperature: 600–1000 °C).

The ranking of the different renewable energy systems proposed in this paper show the most to the least preferable renewable energy system based on the five sustainability criteria (resource, environmental, economic, social and technology) and fourteen subcategories (area, material, energy-construction, energy-fuel, CO2-construction, CO2-fuel, capital-construction, capital-fuel, delivered cost of energy, current installed capacity, growth rate, capacity factor, system efficiency, and lifetime). The final integrated sustainability index is a good indicator and useful assessment tool to determine the best renewable energy technology based on all the sustainability indicators (resources, technology, environmental, economic and social). All the five sustainability criteria were used in

Table 10
The global values of the sub-criteria obtained from CES EduPack and used as an indication of alternatives' performance.

		Solar energy [poly-silicon]	Wind energy [Land-base]	Phosphoric acid fuel cell	Solid oxide fuel cell
1	Capital Intensity (construction) [US$/kW]	4500	1700	3750	7500
2	Capital Intensity (fuel) [US$/kWh]	0	0	0.035	0.024
3	Area Intensity [m^2/kW]	65	275	0.3	0.65
4	Material Intensity [kg/kW]	1500	1250	100	80
5	Energy Intensity (construction) [MJ/kW]	30000	4750	7500	4000
6	Energy Intensity (fuel) [MJ/kWh]	0	0	1.35	0.965
7	CO2 Intensity (construction) [kg/kW]	2250	420	800	300
8	CO2 Intensity (fuel) [kg/kWh]	0	0	0.53	0.35
9	Capacity factor [fraction]	0.1	0.21	0.975	0.975
10	System efficiency [fraction]	0.13	0.45	0.375	0.55
11	Lifetime [yrs]	25	25	9	12.5
12	Current installed capacity [GW]	124	200	0.1	0.1
13	Growth rate [% fraction/yr]	0.4	0.2	0.5	0.5
14	Delivered cost [US$/kWh]	0.175	0.04	0.09	0.09

Table 11
Average grading of the candidates using the geometric mean function (decision-making matrix).

GM	C_{2-2} (CO_2 IN_F)	C_{2-1} (CO_2 IN_C)	C_{3-3} (DLC)	C_{5-2} (EFF)	C_{3-1} (CIN_C)	C_{3-2} (CIN_F)	C_{5-1} (CPF)	C_{5-3} (LFT)	C_{4-2} (GRR)	C_{4-1} (CIC)	C_{1-4} (EIN_F)	C_{1-3} (EIN_C)	C_{1-2} (MIN)	C_{1-1} (AIN)
A0	5.00	4.64	4.22	4.64	4.22	5.00	5.00	4.22	4.64	4.64	5.00	4.22	4.64	5.00
A1	5.00	1.26	1.59	1.00	3.00	5.00	1.00	4.22	3.91	4.00	5.00	1.26	1.26	2.29
A2	5.00	3.63	4.22	3.63	4.22	5.00	2.00	4.22	2.00	4.64	5.00	3.63	2.00	1.00
A3	2.29	2.29	3.30	3.00	3.63	2.00	5.00	1.00	4.64	1.00	1.59	2.29	4.00	5.00
A4	3.30	4.64	3.30	4.64	1.26	3.30	5.00	1.82	4.64	1.00	3.00	4.22	4.64	4.31
sum	20.59	16.47	16.63	16.92	16.33	20.30	18.00	15.47	19.84	15.28	19.59	15.62	16.54	17.60

Table 12
Normalized decision-making matrix.

NM	C_{2-2} (CO_2 IN_F)	C_{2-1} (CO_2 IN_C)	C_{3-3} (DLC)	C_{5-2} (EFF)	C_{3-1} (CIN_C)	C_{3-2} (CIN_F)	C_{5-1} (CPF)	C_{5-3} (LFT)	C_{4-2} (GRR)	C_{4-1} (CIC)	C_{1-4} (EIN_F)	C_{1-3} (EIN_C)	C_{1-2} (MIN)	C_{1-1} (AIN)
A0	0.24	0.28	0.25	0.27	0.26	0.25	0.28	0.27	0.23	0.30	0.26	0.27	0.28	0.28
A1	0.24	0.08	0.10	0.06	0.18	0.25	0.06	0.27	0.20	0.26	0.26	0.08	0.08	0.13
A2	0.24	0.22	0.25	0.21	0.26	0.25	0.11	0.27	0.10	0.30	0.26	0.23	0.12	0.06
A3	0.11	0.14	0.20	0.18	0.22	0.10	0.28	0.06	0.23	0.07	0.08	0.15	0.24	0.28
A4	0.16	0.28	0.20	0.27	0.08	0.16	0.28	0.12	0.23	0.07	0.15	0.27	0.28	0.24

Table 13
Resultant weights of the sub-criteria.

	C_2 (EN)		C_3 (EC)			C_5 (TE)			C_4 (SO)		C_1 (RE)			
w_j	0.277		0.239			0.203			0.160		0.120			
	C_{2-2} (CO_2 IN_F)	C_{2-1} (CO_2 IN_C)	C_{3-1} (CIN_C)	C_{3-2} (CIN_F)	C_{3-3} (DLC)	C_{5-1} (CPF)	C_{5-2} (EFF)	C_{5-3} (LFT)	C_{4-1} (CIC)	C_{4-2} (GRR)	C_{1-1} (AIN)	C_{1-2} (MIN)	C_{1-3} (EIN_C)	C_{1-4} (EIN_F)
w_{ij}	0.099	0.097	0.085	0.081	0.094	0.076	0.089	0.071	0.060	0.066	0.038	0.043	0.048	0.054
$w_j \times w_{ij}$	0.02744	0.02692	0.02033	0.01927	0.02242	0.01546	0.01816	0.01448	0.00958	0.01051	0.00455	0.00516	0.00578	0.00647
$\sum_{i=1}^{i=c} w_j \times w_{ij}$	0.0544		0.0620			0.0481			0.0201		0.0220			
$\sum_{j=1}^{j=5}\sum_{i=1}^{i=c} w_j \times w_{ij}$	0.2065409													
$w_{i,r} = \frac{w_j \times w_{ij}}{\sum_{j=1}^{j=5}\sum_{i=1}^{i=c} w_j \times w_{ij}}$	0.1329	0.1303	0.0984	0.0933	0.1086	0.0749	0.0879	0.0701	0.0464	0.0509	0.0220	0.0250	0.0280	0.0313

Table 14
Weighted normalized decision-making matrix and overall performance index of each alternative.

WOPI	C_{2-2} (CO2 IN_F)	C_{2-1} (CO_2 IN_C)	C_{3-3} (DLC)	C_{5-2} (EFF)	C_{3-1} (CIN_C)	C_{3-2} (CIN_F)	C_{5-1} (CPF)	C_{5-3} (LFT)	C_{4-2} (GRR)	C_{4-1} (CIC)	C_{1-4} (EIN_F)	C_{1-3} (EIN_C)	C_{1-2} (MIN)	C_{1-1} (AIN)	Sa
$\boldsymbol{w_{i,r}}$	0.1329	0.1303	0.1086	0.0879	0.0984	0.0933	0.0749	0.0701	0.0509	0.0464	0.0313	0.0280	0.0250	0.0220	
A0	0.032	0.037	0.028	0.024	0.025	0.023	0.0208	0.019	0.012	0.0141	0.0080	0.0076	0.0070	0.0063	0.221
A1	0.032	0.010	0.010	0.005	0.018	0.023	0.0042	0.019	0.010	0.0121	0.0080	0.0023	0.0019	0.0029	0.159
A2	0.032	0.029	0.028	0.019	0.025	0.023	0.0083	0.019	0.005	0.0141	0.0080	0.0065	0.0030	0.0013	0.221
A3	0.015	0.018	0.022	0.016	0.022	0.009	0.0208	0.005	0.012	0.0030	0.0025	0.0041	0.0060	0.0063	0.160
A4	0.021	0.037	0.022	0.024	0.008	0.015	0.0208	0.008	0.012	0.0030	0.0048	0.0076	0.0070	0.0054	0.195

Table 15
Overall results of the ranked alternatives

	S_a	Q_a	*Rank*
A_0	0.221		
A_1	0.159	0.72	4
A_2	0.221	1.00	1
A_3	0.160	0.73	3
A_4	0.195	0.88	2

this analysis and not one criteria alone. The final ranking will be different if only one criteria is used in the analysis (example – economic analysis of solar PV, wind, and fuel cell). It is also noted that several renewable energy systems are planned together (hybrid renewable power system). The present study includes the determination of sustainability indicators of each renewable energy system alone using multi-criteria decision-making model. The authors are working on developing new sustainability indicators for hybrid renewable energy systems using multi-criteria decision-making model. Future works will include the ranking of the hybrid renewable power systems such as solar PV/wind, solar PV/fuel cell, Wind/fuel cell, solar PV/Biomass, and Biomass/wind.

5. Conclusion

This study has been performed to assess four renewable energy systems against five main sustainability indicators and their fourteen sub-criteria. The assessed technologies were Land-based wind energy systems, solid oxide fuel cells, phosphoric acid fuel cells, and poly-silicon solar energy systems. The main sustainability indicators were environment, economy, society, technology, and resource indicators. The sub-criteria against which the selected renewable power technologies assessed were: area intensity, material intensity, energy intensity (construction), energy intensity (fuel), CO_2 intensity (construction), CO_2 intensity (fuel), capital intensity (construction), capital intensity (fuel), delivered cost of

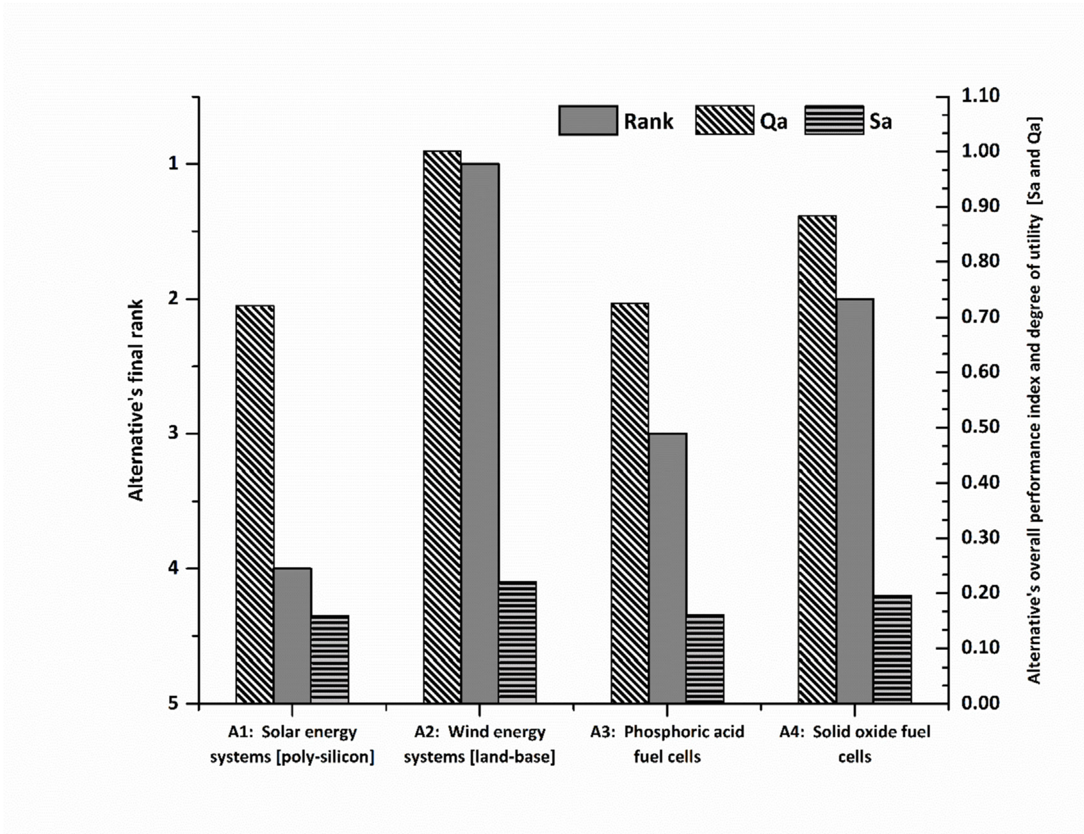

Fig. 8. Final ranking of the selected renewable energy technologies.

energy, current installed capacity, growth rate, capacity factor, system efficiency, and lifetime. These main indicators and their sub-categories formed the multi-criteria decision-making model. A Hybrid method, which is the Extended Step-wise Weight Assessment Ratio Analysis, was used to evaluate the importance of the sustainability indicators and their sub-criteria by three energy experts according to the current state of environment, economy and society. This evaluation is combined with the Additive ratio assessment method to assess the performance of the selected renewable power systems with respect to the evaluation criteria by the same three experts. The performance of such technologies was referenced to the global values provided by CES EduPack. The final results of the study showed that land-based wind energy systems are ranked first with respect to sustainability indicators and their sub-indicators, followed by solid oxide fuel cells, then phosphoric acid fuel cells, and lastly polysilicon solar energy systems.

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Appendix A

A1. Classical Step-wise Weight Assessment Ratio Analysis (SWARA) Method

Step 1: a group of experts propose several evaluation criteria and sort them in a descending order based on their expected significance. Then each expert gives an importance percentage ratio for each criterion as a multiple of 5% to represent its significance with respect to other criteria based on his/her experience.

Step 2: starting from the second criterion, the difference in the significance ratio between criterion j and j-1 is calculated to show how criterion j-1 is more important than criterion j. According to Keršulien [18], this is called the comparative importance of the average value s_j [18].

Step 3: The coefficient k_j is calculated as follows;

$$k_j = \begin{cases} 1 & j = 1 \\ s_j + 1 & j > 1 \end{cases}$$

Step 4: The recalculated weight q_j is obtained as follows;

$$q_j = \begin{cases} 1 & j = 1 \\ \dfrac{q_{j-1}}{k_j} & j > 1 \end{cases}$$

Step 5: The relative weights w_j of the evaluation criteria are determined as follows;

$$w_j = \frac{q_j}{\sum_{m=1}^{n} q_m}$$

where n denotes the number of the evaluation criteria.

A2. Ranking of the main sustainability indicators and their sub-indices by the three experts

Table A 2.1
Ranking of the main sustainability indicators based on the significance level from the three experts

Rank values t_{jk}, *j* = 1, …., *n*, *n* = 5					
Expert k = *1-3*	*Proposed criteria*				
	C_1 (RE)	C_2 (EN)	C_3 (EC)	C_4 (SO)	C_5 (TE)
1	5	1	2	4	3
2	5	1	3	4	2
3	5	1	2	4	3

Table A 2.2
Ranking of the sub-criteria of the main sustainability indicators based on the significance level from the three experts

Rank values t_{ik}, *i* = 1, …., *b*, *b* = 14														
Expert k = *1-3*	Proposed sub-criteria													
	C_{1-1} (AIN)	C_{1-2} (MIN)	C_{1-3} (EIN_C)	C_{1-4} (EIN_F)	C_{2-1} (CO_2 IN_C)	C_{2-2} (CO_2 IN_F)	C_{3-1} (CIN_C)	C_{3-2} (CIN_F)	C_{3-3} (DLC)	C_{4-1} (CIC)	C_{4-2} (GRR)	C_{5-1} (CPF)	C_{5-2} (EFF)	C_{5-3} (LFT)
1	14	11	13	12	2	1	5	4	3	10	9	7	6	8
2	14	13	12	11	2	1	7	8	6	10	9	4	3	5
3	14	13	12	11	2	1	4	5	3	10	9	7	6	8

A3. Experts' evaluation grades of the selected evaluated renewable energy technologies

Table A 3.1
Grading obtained from the first member of DM's

1	C_{2-2} (CO_2 IN_F)	C_{2-1} (CO_2 IN_C)	C_{3-3} (DLC)	C_{5-2} (EFF)	C_{3-1} (CIN_C)	C_{3-2} (CIN_F)	C_{5-1} (CPF)	C_{5-3} (LFT)	C_{4-2} (GRR)	C_{4-1} (CIC)	C_{1-4} (EIN_F)	C_{1-3} (EIN_C)	C_{1-2} (MIN)	C_{1-1} (AIN)
A1	5	1	2	1	3	5	1	5	3	4	5	1	1	2
A2	5	4	5	4	5	5	2	5	2	5	5	4	2	1
A3	3	3	4	3	4	2	5	1	4	1	2	3	4	5
A4	4	5	4	5	1	3	5	2	4	1	3	5	5	4

Table A3.2
Grading obtained from the second member of DM's

2	C_{2-2} (CO_2 IN_F)	C_{2-1} (CO_2 IN_C)	C_{3-3} (DLC)	C_{5-2} (EFF)	C_{3-1} (CIN_C)	C_{3-2} (CIN_F)	C_{5-1} (CPF)	C_{5-3} (LFT)	C_{4-2} (GRR)	C_{4-1} (CIC)	C_{1-4} (EIN_F)	C_{1-3} (EIN_C)	C_{1-2} (MIN)	C_{1-1} (AIN)
A1	5	1	1	1	3	5	1	5	4	4	5	1	1	2
A2	5	4	5	4	5	5	2	5	2	5	5	4	2	1
A3	2	2	3	3	4	2	5	1	5	1	1	2	4	5
A4	3	5	3	5	1	3	5	3	5	1	3	5	5	4

Table A 3.3
Grading obtained from the third member of DM's

3	C_{2-2} (CO_2 IN_F)	C_{2-1} (CO_2 IN_C)	C_{3-3} (DLC)	C_{5-2} (EFF)	C_{3-1} (CIN_C)	C_{3-2} (CIN_F)	C_{5-1} (CPF)	C_{5-3} (LFT)	C_{4-2} (GRR)	C_{4-1} (CIC)	C_{1-4} (EIN_F)	C_{1-3} (EIN_C)	C_{1-2} (MIN)	C_{1-1} (AIN)
A1	5	2	2	1	3	5	1	3	5	4	5	2	2	3
A2	5	3	3	3	3	5	2	3	2	4	5	3	2	1
A3	2	2	3	3	3	2	5	1	5	1	2	2	4	5
A4	3	4	3	4	2	4	5	1	5	1	3	3	4	5

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