An integrated simulation-optimization modelling approach for sustainability assessment of electricity generation system

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Abstract

Devising a concrete plan for power supply should conduct the best technology-capacity-time strategy while satisfying fuel, infrastructure, and trading constraints. Addressing sustainability concerning stakeholders' opinions aligned with upstream policies escalates the problem, demanding new reliable frameworks. This paper aims to develop an integrated simulation-optimization decision support system for electricity generation planning. A differential evolution algorithm simulates the future power supply configurations. A linear programming model characterizes the optimal pathways towards those futures. Multi-criteria decision-making methods are also included for determining the preference weights of sustainability indicators and ranking the scenarios. The proposed framework offers a sustainable plan for Iran by 2050. The sustainability criteria are tracked and compared with a business as usual (BAU) scheme. The results show that the broader deployment of wind turbine primarily, solar thermal subsequently, is the major source of difference in the sustainable expansion compared to BAU. Those technologies along with photovoltaics, contribute to 48% of the generation at the end of the planning horizon. However, the findings indicate that even the extensive utilization of renewable energy sources cannot guarantee sustainability improvement all through the planning period. Thus, supply-side plans should be appropriately supported by demand-side strategies.

Keywords: Sustainability, Renewable electricity, Simulation, Optimization, Evolutionary algorithm

1. Introduction

In the age of electricity, there is a strong need for a well-thought-out and workable plan to pave the way for sustainability in power supply [1]. However, designing a solid plan is a challenging task due to some reasons: (i) variety in types of power generation technologies in terms of energy sources and techno-economic parameters; (ii) social and environmental conflicts arising from the utilization of different technologies [2]; (iii) fuel, investment, trading, and infrastructure constraints [3]; (iv) diverse stakeholders' interests and requirements; and (v) upstream goals and policies [4]. Some of these aspects cab be addressed by using the Energy System Models (ESMs), but the examination of multiple decision variables significantly escalates the problem. Characterizing a reliable configuration—what type, how much, and when to install power generation plants—calls for a state-of-the-art and integrated modelling approach that adequately captures individual characteristics and the intricate interdependencies.

Simulation and optimization are two principal methodologies used for the development of energy models [5]. The primary concentration in optimization models is on the current system's configuration as a starting point, and procedures are followed afterwards to identify the optimal pathway ahead [6]. In this way, optimization models are suitable for forecasting. Satisfying the problem's constraints in these models, the energy system's interactions create a feasible region, and the goal is to seek the optimal solution within the region. The optimal solution is explored in the direction of the objective function that is typically cost minimization. Negative environmental impacts are sometimes considered as a cost term in the objective function [7]. Due to the quasi-dynamic nature of energy supply problems in which the interaction between periods is issue, mathematical optimization techniques are the most prevalent methods used in this field (a detailed review on energy system optimization models is contained in [8] [9]).

Optimization has numerously been employed either in energy system tools—that are available as a computer-based software—or user-developed models—that their formulations are presented by researchers and should be coded by users. TIMES, MESSAGE, and MARKAL are some of the most well-known energy system tools that have been frequently hired to facilitate electricity policy-making. User-developed models also have been adapted in a variety of researches, for example, for long-term energy and power planning in Greece [10], making trade-offs between carbon emissions and job creation in Iran's power sector [11], analyzing the effects of temporal divisions on electricity sector planning in China [12], investigating future pathways for power supply's cost and carbon in the UK [13], and evaluating the adequacy of local energy sources in

Indonesia [14]. The ability to carefully match the scale and scope of the problem and the easiness to use are particular advantages of the user-developed optimization models [15].

In simulation models versus optimization, a logical representation of a system describes the simplified operation of that system [5]. As a kind of scenario model, simulation methods are often used to analyze and compare scenarios. The details of the current system arrangement in these models are less significant than optimization, while the prospect options' components are indispensable. This characteristic makes simulation well-suited for backcasting [6]. Backcasting includes designing desired future scenarios, i.e., normative scenarios, and planning backward to explore which transition pathways lead to those desired futures [16]. Some recent studies have used simulation models to design power supply strategies (e.g., [17] [18]).

Taking sustainability indicators into consideration makes energy planning problems more complicated because the ultimate plan should be satisfactory respecting conflicting outlooks. Accordingly, there is a need to upgrade the existing energy analysis frameworks. Taking advantage of simulation principles into optimization models could be a significant effort. In this regard, the common methodology includes defining a set of future scenarios, identifying the best configuration of each scenario, and finally assessing and comparing the scenarios in association with the sustainability criteria. Over the past few years, this framework has been the dominant foundation for sustainable power supply planning and received enormous attention. Based on that method, for instance, Volkart et al. [19] evaluated climate protection scenarios in the Swiss energy sector, and Rosso-Cerón et al. [20] appraised power generation alternatives in San Andrés, Colombia,

Nevertheless, the past efforts can be considered a small step towards incorporating simulation into optimization. In most of the previous works, a small number of scenarios have been examined. In practice, however, more than a few future scenarios should be evaluated, as simulation models do. Many countries in their national energy policy address a long-term approach. Given that they provide only a broad outline, policies need to be accompanied by a detailed plan with specific and measurable targets. Accordingly, a lot of future scenarios could be in accordance with the policies. Identifying the most fitting scenario, thus, is crucial to make available an executive and trackable plan in association with the upstream policies.

This paper aims to move one step more towards combining simulation and optimization models, merging forecasting and backcasting. Few previous works have developed this idea. Rodgers et al. [21] used a simulated generation expansion planning (GEP) model to mitigate health risks. Piao et al. [22] integrated the Monte Carlo simulation, support-vector-regression, and inexact chance-constrained programming techniques to deal with uncertainty. Mahbub et al. [23] coupled EnergyPLAN with a multi-objective genetic algorithm (GA) to minimize cost and carbon emissions. Bjelić and Rajaković [24] used EnergyPLAN aligned with the generic optimization program (GenOpt) to explore renewable energy sources. The present study integrates simulation and optimization in a novel initiative. Specifically, the goal is to incorporate simulation approaches' precious ability in searching numerous future scenarios into optimization models. For this purpose, an efficient evolutionary algorithm (EA) is brought into play. EAs as artificial intelligence techniques are robust tools in solving complex search problems [25].

Using an EA could merge simulation into optimization. The remaining problem is how various scenarios be appraised in the presence of different sustainability factors. Multi-criteria decision-making (MCDM) methods are recognized as practical means that have recently gained wide applications for multi-metric sustainability evaluation [26]. In energy and electricity systems analysis, MCDMs can be hired in two manners, one determining the importance of criteria and assigning weights to them during which concerning goals [27], and another ranking the alternatives (scenarios [28] or technologies [29]) while regarding the criteria. In the former use, experts' and stakeholders' opinions and interests are included in the decision-making process. This paper utilizes the Analytic Network Process (ANP) [30] to convert qualitative experts’ judgments into quantitative criteria weights. Besides, VIKOR [31] is applied to assess and rank the scenarios in connection with the overall sustainability performance.

The proposed framework is put into practice to draw a sustainable expansion design for Iran. Iran is a key player in the global energy supply scene as it possesses the largest oil and gas reserves worldwide [32]. On the other hand, the country's per capita energy consumption is ten times the European Union [33]. Enormous accessible oil and gas resources have been the root cause of the overreliance of the country's power sector on fossil fuels, where 93% of electricity comes from fossil-based power plants [34]. This electricity mix is a crucial reason to bring the country among the world's top ten GHG producers [35], because over 30% of the total GHG stems from electricity generation activities [36]. However, the country presumably has a bright energy supply perspective since it benefits from a wide variety of renewable resources in abundance. The current mix's leading renewable resource is water, with a 4.9% share in the generation. Non-hydro renewables such as solar, wind, geothermal, and biomass totally have a negligible contribution of 0.1%. They could be put on the map more seriously, especially if we know that two-thirds of Iran's area has above 300 days of sunshine annually [37], east and northwestern regions are in the path of strong winds [38], and close to 9% of the land has the geothermal potential [39].

In summary, the present work makes distinctive contributions through the following ways:

- Proposing a decision support system based on a state-of-the-art simulation-optimization framework for sustainable electricity supply planning passing through integrating a differential evolution algorithm, a linear programming (LP) model, and a combined ANP-VIKOR.
- Devising a long-term sustainable power expansion plan in which the trend of sustainability indicators is tracked and assessed.

The paper's outline is as follows: Section 2 explains the methodology used to derive the sustainable plan. Section 3 examines the applicability of the proposed framework for the case of Iran. Section 4 analyzes the results of electricity generation pathways and sustainability indicators trend. In Section 5, the results are tested and compared with some previous works. Finally, Section 6 provides conclusions and main insights.

2. Methodology

The schematic of the proposed methodology is illustrated in Fig. 1. The methodology can be used to determine which technologies to what extent should be employed to achieve sustainability in the power supply. It provides sustainable generation and capacity pathways for a country or region based on the experts' and stockholders' opinions. By utilizing the framework, it is possible to assess the sustainability measures through a long planning horizon. The methodology uses an artificial intelligence technique combined with an optimization model and MCDM tools. This integration provides the ability to automatically generate normative scenarios and evaluate them in terms of overall sustainability. This is a step forward in the transition from cost-concentration modeling frameworks to sustainability-focused ones. Almost all of the existing energy systems tools

(TIMES, etc.) are based on cost and the proposed methodology could be a source of idea to extend those models towards sustainability.

The proposed framework consists of four steps that based on some inputs and assumptions gives rise to a sustainable plan in an iterative manner. Inputs include electricity demand projection, techno-economic parameters of power generation technologies, fuel prices, trading costs, and grid losses. As the aim is addressing sustainability, environmental and social data are also regarded as input. Experts' judgments are another input that is required to provide a sustainable arrangement. Since sustainability depends on a region where planning is undertaking, the opinion of local, knowledgeable people regarding the significance of indicators is determinative. The share ranges of technologies in the planning horizon is the other data used for simulation and could be sourced from the upstream policies or the previous analyses. Besides, each step results in an output that plays an input role for the next step. The note is that steps 2 to 4 comprise an iterative process that continues until a stop criterion is met.

Fig. 1. The schematic representation of the proposed simulation-optimization framework.

2.1. Step 1. Indicator weighting

The ANP method derives the comparative importance of indicators. As a general form of the Analytic Hierarchy Process (AHP) method, the ANP relies on a network of relationships rather than a hierarchy. The network structure makes it possible to consider the interdependencies between elements within a decision making problem [30]. Accordingly, it would be a suitable tool to deal with multiple sustainability indicators that are sometimes co-dependent in nature. The influence of indicators in a network could be accounted for not just in a top-down arrangement but also in other directions.

A network includes clusters, elements, and arcs. Elements categorized in clusters, are connected by arcs in the same or other clusters to show dependencies according to the problem specifications. The experts' opinions regarding the relative preferences of the decision elements are acquired through pairwise comparisons in which two elements are compared concerning a controlling factor. The elements' weights are computed as the same procedure as AHP (see [40] for AHP calculations). The consistency ratio is a reliable index to figure out whether judgments are reasonable. The priorities resulting from pairwise comparison matrices compose a supermatrix that each of its segments represents a relationship between two clusters. The relative importance of the clusters in the supermatrix is computed to derive the absolute priorities. The comparison of rows is then made to obtain first, eigenvectors, next, the weighted supermatrix. To converge the weights, the supermatrix is raised to the power of a large number, and the result is called the limit supermatrix. By normalizing this matrix, the final weights are gained (see [41] for the detailed procedure).

The network in this study encompasses three clusters. The first corresponds to the decision problem's goal, which is sustainability in the power supply sector. The second cluster involves major sustainability dimensions, including economic, technical, environmental, and social. The last cluster includes the sub-criteria of sustainability dimensions that appear as the role of alternatives, and the aim is to determine their weights. The interdependencies and relationships between the elements are specified, and pairwise comparisons are carried out. It deserves to mention that breaking down the techno-economic dimension into two distinct economic and technical aspects decreases the necessary pairwise comparisons and subsequently boosts the consistency.

2.2. Step 2. Scenario definition

In order to define the scenarios, a differential evolution (DE) algorithm is brought into play. The DE algorithm is used to outline the future configuration of the power system—this is the way also is used in some other simulation-based energy systems tools for example EnergyPLAN. According to scenario-based planning concepts, these configurations are called normative scenarios. Using the DE in the mentioned way provides a foundation for simulation because the rest of the methodology in a backward move seeks optimal pathways towards those normative scenarios. More clearly, this process, i.e., generating future power scenarios and finding pathways towards them backwardly, has been referred to as a simulation process.

DE is a competitive stochastic search method developed initially to solve continuous problems and has been frequently used to solve various complicated search problems [42]. As an evolutionary algorithm, DE iteratively regenerates populations of solutions by implementing some operators through which the populations' members are gradually modified and finally converged to the fittest solution. The solutions are evaluated based on a fitness function that classically is a single-objective optimization. Like the GA [43], DE relies on three operators, namely mutation, crossover, and selection, but in an upgraded structure and order. In the DE process, each member of the current population is considered a target vector, and the operators are implemented regarding each of them. Within mutation, the weighted difference of some of the randomly selected vectors is added to another one to create the mutant vector. The crossover operator is applied afterwards to generate the trial vector by mixing the mutant and target. At last, the fittest vector among the trial and target is admitted within the selection operator to transfer to the next generation [44].

Depending upon the vector selection strategy, the number of used difference vectors, and the crossover type, different versions for DE exist. In this paper, DE/best/2/bin is taken up, meaning that the weighted difference of two pairs of vectors is added to the best individual to produce the mutant vector, and then structuring the trial is done using a binomial crossover. The reasons for making use of DE in general and the mentioned version, in particular, are proven performance in solving complex continuous problems, keeping diversification in population and avoiding premature convergence, few control parameters (population size, crossover rate, and scaling factor), in-built elite strategy (preserving the best member of the previous generation), and finally well matching of the operators' structure with the problem representation [45] [46].

Each scenario corresponds to a chromosome (vector or individual) in the context of the DE literature. A scenario refers to a generation mix at the end of the planning horizon and determines a lower bound of the share of different categories of technology. In this way, the DE helps regulate the minimum share of technology from a predefined range. It is noticeable that specifying a predefined range can be skipped, but keeping it reduces the search space and hinders the creation of undoubtedly unacceptable portfolios. So, it helps reach an optimal solution at a faster pace. Each scenario then works as a constraint in the optimization model in the next step. Running the DE is initiated in this step, but it continues in the next steps to shape its loop. The solution representation, i.e., the chromosome, is organized as a string of real numbers that each gene stands for a share of a specific type of technology. Fig. 2 illustrates the structure of a chromosome.

Fig. 2. Solution representation scheme in the designed DE algorithm.

The pseudo-code for the proposed DE is as follows:

Begin

Generate a random population of chromosomes (consists of n-pop members)

Set the generation counter *G* equal to 0

while (the termination condition is not true)

Set $G = G + 1$

for $i = 1$: n-pop

Do mutation to create mutant vector

Do crossover on mutant and target i to create the trial vector

Rank the trial and target and find the current best

Accept the current best as the ith member of the population in generation G

end for i

end while

Output the best member in generation G

End

For each target vector i in the current population (x_i^G), the mutant vector v_i^{G+1} is generated by putting into operation the following mutation operator:

$$v_i^{G+1} = x_{best}^G + F\left(x_{r1}^G + x_{r2}^G - x_{r3}^G - x_{r4}^G\right) \tag{1}$$

where subscript *best* refers to the best-ranked individual in the population, r_1, r_2, r_3, and r_4 are randomly chosen numbers from the set $\{1.2. \ldots n - pop\}$, and F is a real constant scaling factor from U[0 1]. The mutant vector is formed based on the mutation formulation, relying on the best individual in the current population. Its genes however are changed by adding a weighted difference of four randomly selected vectors. This procedure keeps the diversification of the population in a reasonable range.

The genes *(j=1, 2, …, D)* of the trial vector u_i^{G+1} are specified via combining the target vector x_i^G with the mutant vector v_i^{G+1} by executing the following crossover operator:

$$u_{j,i}^{G+1} = \begin{cases} v_{j,i}^{G+1} & if\ \left(rand\left(j\right) \le CR\right) or\ j = rndI \\ x_{j,i}^{G} & if\ \left(rand\left(j\right) > CR\right) and\ j \ne rndI \end{cases} \tag{2}$$

where *rand (j)* is a real random number in U[0 1], *CR* denotes the crossover rate, and *rndI* is an integer random number from $\{1.2. \ldots.\ D\}$, which guarantees $u_i^{G+1} \ne x_i^G$ [44].

2.3. Step 3. Power supply optimization

In order to derive the optimal capacity expansion pathway, the Reference Energy System (RES) comprising the flows from energy resources to end-use demands is optimized through developing and solving the corresponding LP model. The model includes an objective function representing the net present value of different cost elements including investment cost, operation and maintenance (O&M) cost, trading cost, fuel cost, decommissioning cost, and grid cost. The objective function is subject to a set of constraints involving electricity demand, power generation, fuel availability, infrastructure capacity, and trading limitation. The model adapted from [11] [14] [13] is provided in Appendix A.

The maximum share of different technologies regulated by a scenario is embedded in the LP model by the following constraint.

$$G_{i,t_{end}} \leq \varepsilon_{i,t_{end}} \left(\sum_{i \in I} G_{i,t_{end}}^{New} + \sum_{i \in I} G_{i,t_{end}}^{Ext} \right) \quad \forall i \in I \tag{3}$$

where $G_{i,t_{end}}$ refers to the electricity generation by technology type *i* in the last period of planning, $\varepsilon_{i,t_{end}}$ denotes the share of technology *i* at the end of the planning horizon, *I* is the set of all types of power plants, and *New* and *Ext* imply the new and existing technologies, respectively. As a result of the inequality above, each scenario in a population of solutions leads to a different capacity transition plan.

2.4. Step 4. Scenario ranking

After shaping the power supply configurations corresponding to the scenarios, it should be examined which scenario is the most preferred in the presence of multiple indicators. To accomplish this, VIKOR, as an MCDM tool, is utilized, wherein scenarios play the role of alternatives. Based on an L_p-metric aggregating function [47], VIKOR formulates the utility (S_j in Eq. (4)) and regret (R_j in Eq. (5)) measures to rank an array of alternatives concerning a group of contradictory criteria to give rise to a (set of) compromise choice(s). A compromise choice gives the most group utility of the majority and the least individual regret. Closeness to the ideal choice as the fundamental principle in VIKOR is quantified by using the ranking measures [31]. Relative to other similar MCDM methods, the high ability of VIKOR to select the ideal alternative in terms of the various sustainability indicators [48] is the motivation of this study to put it into work.

To take an overview of the VIKOR model, assume that f_{ij} represents the performance of alternative *j* (*j=1,2, …, m*) according to criterion *i* (*i=1,2, …, n*). The subsequent $m \times n$ decision matrix is normalized to remove the units of criterion functions, and the procedure below is followed.

Step 1. Determining the best f_i^+ and the worst f_i^- values for all criteria:

$f_i^+ = \max_j f_{ij}$; $f_i^- = \min_j f_{ij}$ if *i* is a positive criterion (the higher value, the better performance)

$f_i^+ = \min_j f_{ij}$; $f_i^- = \max_j f_{ij}$ if *i* is a negative criterion (the lower value, the better performance)

Step 2. Calculating the utility measure S_j and the regret measure R_j :

$$S_j = \sum_{i=1}^{n} w_i \left(f_i^+ - f_{ij}\right) / \left(f_i^+ - f_i^-\right) \tag{4}$$

$$R_j = \max_i \left[w_i \left(f_i^+ - f_{ij}\right) / \left(f_i^+ - f_i^-\right) \right] \tag{5}$$

where w_i is the weight of criterion *i* assigned by the ANP method.

Step 3. Computing the VIKOR index Q_j :

$$Q_j = \frac{v\left(S_j - S^+\right)}{\left(S^- - S^+\right)} + (1-v)\frac{\left(R_j - R^+\right)}{\left(R^- - R^+\right)} \tag{6}$$

where $S^+ = \min_j S_j$, $S^- = \max_j S_j$, $R^+ = \min_j R_j$, $R^- = \max_j R_j$, and v is the weight of the maximum group utility strategy and is assumed to be 0.5 [49].

Step 4. Sorting the alternatives according to Q, S, and R values in descending order and accepting a choice with the lowest *Q* value as the compromise solution. Checking "acceptance advantage" and "acceptable stability in decision-making" conditions [31] regarding *S* and *R* arrays also is suggested to determine whether multiple compromise solutions are available.

3. Demonstration of the proposed methodology for the case of Iran

As the most important Iranian government department for power supply, the Ministry of Energy (MOE) is responsible for the regulation and implementation of policies for energy, electricity, water, and wastewater services. Besides, the Ministry of Petroleum is the other critical organ that supervises exploration, extraction, marketing, and selling crude oil, NG, and petroleum products via its subsidiaries. Iran High Energy Council has been established to make a concentration in policymaking by coordinating policies of the whole energy sector through contributing MOE, Ministry of Petroleum, and other relevant ministries.

There are two main holding companies supervised by the MOE: (1) Power Transmission, Generation, and Distribution Company (Tavanir) and (2) Thermal Power Plants Holding Company. The former deals with management and supervision on the installation and operation of power system facilities. The latter organizes government enterprise activities in thermal power generation. At a more operational level, there are regional electric companies, power distribution companies, power generation management companies, Iran Grid Management Company (IGMC), Iran Power Plant Project Management Company (MAPNA), and Renewable Energy and Energy Efficiency Organization (SATBA). They are in charge of the implementation of the plans and programs [50].

The proposed framework is put into play to prepare a sustainable plan for Iran's electricity supply sector. A 30-year planning period is considered from 2020 to 2050. According to the current condition and future potential of resources and infrastructure, a set of 18 electricity generation technologies including the steam power plant, combined cycle technology (conventional and advanced), gas turbine (conventional and advanced), gas engine (off-grid), coal-fired power stations (conventional and advanced), nuclear power plant (conventional and advanced), hydropower (small and large), wind turbine, solar photovoltaic (on- and off-grid), solar thermal, geothermal, and biomass (landfill) is determined as the candidates. The sustainable pathway is aimed to devise according to 16 indicators.

3.1. The sustainability indicators weights

A detailed review analysis on the sustainability assessment of power generation [51] [52] shows that most previous studies considered three dimensions (i.e., techno-economic, social, and environmental indicators). However, as mentioned by Santoyo-Castelazo and Azapagic [51], the number of indicators are significantly different, ranging from four [53] to 75 indicators [54]. After extensive engagement with multiple stakeholders from academic centers to industrial sectors and governmental organizations, 16 different indicators have been selected in this paper. Each indicator addresses the most critical problems facing Iran during recent years.

To gain the preference weights by using the ANP method, the indicators and the relations network are characterized as Fig. 3. The description of the indicators has been provided in Table 1. The network includes three clusters, which are goal, criteria, and alternatives. The goal cluster encompasses one element that aims to address sustainability in Iran's power supply. The criteria cluster has four elements referring to sustainability aspects. The alternative cluster includes the operational indicators whose importance weights are the main issue. Arcs show the relationships between the elements. The goal is connected to the four sustainability aspects, and then each of the aspects is connected to relevant indicators. Besides, some economic indicators are selfconnected to consider interdependencies. For instance, the arc from the LCOE to investment cost denotes that the former depends on the latter. The required pairwise comparisons resulting from the network structure are carried out by experts based on a numerical scale from one to nine, where the more significant number indicates the higher preference. The valid outputs resulting from SuperDecisions software are shown in Fig. 4.

Fig. 3. Sustainability indicators and their relationship network in the ANP method.

Table 1. The description of the sustainability indicators [55].

Fig. 4. Sustainability indicators' weights for the case of Iran.

3.2. Solution representation

The assumed set of power generation technologies are categorized into nine groups. Subsequently, the chromosome in the DE algorithm includes nine genes representing the share of different categories of technologies in electricity supply at the horizon 2050. The share range of each group, given in Table 2, is determined according to the country's potential and the previous studies.

Table. 2. The groups of technologies and their range of share in 2050 generation [56] [57] [11] [58] [59].

3.3. Data

Iran's electricity demand is projected to grow by a 3.8% annual average rate reaching from the current 280 to 854 TWh in 2050 [60]. The transmission and distribution losses that currently are about 10.4% and 2.8%, respectively, are expected to decrease to 2.5% and 6.0% at the horizon 2050 [61]. Per megawatt-hour, electricity distribution cost is around \$8.3, and that for transmission is near \$8.9 [62]. At present, the import and export shares account for at most 1.3% and 3.8% of the overall generation and can rise to 5% and 10% by the end of the planning period. Electricity import cost and export price are assumed to be 60 \$/MWh and 80 \$/MWh at present, both with a growth rate of 1.8% by 2030 [61] [36]. The limitation of natural gas (NG) contribution from the current 70% steadily relaxes by 2030 [57]. NG, fuel oil, diesel, and thermal coal prices are assumed to be 0.28, 0.52, 0.75, and 0.19 cents/MJ with a 1.1% yearly increase rate [32] [63] and nuclear fuel cost is set on 1 cents/kWh [64]. The techno-economic parameters and the environmental and social factors of the power generation technologies are provided in Appendix B.

4. Results

GAMS/CPLEX was used to solve the LP model, and MATLAB software was employed to run the DE algorithm in a link with GAMS's outputs. After primary runs, the population size was set on 20, and the crossover rate was determined as 0.4 so that the algorithm converged in 150 generations. In addition to the sustainable plan, the business as usual (BAU) scheme was also arranged in which the ongoing development was continued. The two expansion plans were analyzed and compared in terms of power supply transitions and sustainability indicators trends.

4.1. Capacity and generation expansion

The optimal capacity pathway and its corresponding gross generation for BAU and sustainable schemes are depicted in Fig. 5. The BAU's total installed capacity is expected to grow with a 3.8% average annual rate reaching 229 GW by 2050. Thanks to the low NG price and conversion efficiency improvement, the combined cycle holds its dominion. With a 78 GW capacity, 54% of the generation at the end of the model horizon comes from that technology. Concerning the other fossil fuel technologies, the existing steam power plants are gradually phased out, and gas turbine and coal power plant preserve their marginal share. Over time, renewable technologies become economically competitive and gain an essential role in the portfolio. Wind turbine is the leading renewable source that continues its accelerating penetration and reaches 13% in generation due to 48 GW capacity. Solar PV is the next promising renewable with a 55 GW capacity, i.e., 9% share in the generation.

The sustainable scheme's overall capacity shows a 4.6% year-on-year average growth that finally reaches 288 GW in 2050, 26% more than BAU. The more significant contribution of renewable technologies with lower availability factors is the reason behind that increase. Like BAU, the combined cycle is the dominant technology but with less significance. After reaching 58% in 2030, its generation share reduces to 36% by 2045 and rises again to 37% in the ending years, satisfying the escalating demand. The sustainable plan accelerates the adoption of clean and renewable technologies, especially wind turbines, compared to the BAU. Over the medium- to long-term, wind turbine capacity increases markedly and touches 83 GW, making it the most favorable renewable. The total share of non-hydro renewables in the generation is 49% in 2045 and stabilizes at this level by 2050. Solar thermal and hydropower altogether with near 48 GW capacity are necessary to meet a demand portion. With 58%, the share of CO_2 free electricity in the sustainable strategy is 27% greater than that of BAU.

Fig. 5. Capacity and generation pathways in the BAU and sustainable schemes up to 2050.

Fig. 6 highlights the generation mix differences in scenarios. Out of the total 945 TWh generation in 2050, there is 254 TWh, i.e., near 27% difference in energy sources in the two schemes. Before 2030, there is no substantial discrepancy in the expansion pathways. After that, the generation mostly stemmed from the combined cycle in BAU, substituted in the sustainable plan first by the wind turbine, then solar thermal, and finally solar PV. In the last period of the sustainable plan, wind turbine and solar thermal generate 93 and 81 TWh more electricity than in the BAU. Solar PV is another source that makes a difference and plays a more critical role in the sustainable plan with around 57 TWh more generations.

Fig. 6. Change in electricity generation source due to development scheme.

4.2. Sustainability indicators outlook

In this section, the sustainability indicators trends throughout the planning period are traced in a comparative representation between BAU and sustainable schemes.

4.2.1. Techno-economic indicators

The fluctuations of techno-economic indicators from 2020 to 2050 is shown in Fig 7.

Investment cost

In the first year of planning, the investment cost is calculated as 2.44 cents/kWh. Before 2030, it remains almost flat at the same level as 2020 in the two plans. A slight increase in BAU is observed afterward, ultimately leading to 2.58 cents/kWh in 2050. In the sustainable plan, however, a higher tendency is towards capital-intensive technologies. In that plan, a sharp increase occurs from 2030 onwards; thereby, the cost rises above 38% and reaches 3.38 cents/kWh, driven by a substantial increase in nuclear power and renewables, especially wind and solar thermal. In line with the declining share of clean technologies within the last periods, the investment cost falls around 0.23 cents and stabilizes at 3.15 cents/kWh in 2050.

Fuel cost

While both BAU and sustainable plans present a similar pattern in fuel cost, the latter shows lower levels after 2030. In BAU, fuel cost declines from 3.18 to 2.60 cents/kWh during 2020-2045 and rises again to 3.02 at the ending period. Moving towards renewable energies in the sustainable plan causes less fuel consumption and lower per-unit electricity fuel costs. At its minimum level, the sustainable scheme's fuel cost is expected to be 1.87 cents/kWh. In 2050, it would be 2.14 cents, 29% less relative to BAU.

O&M cost

In both scenarios, O&M costs follow an increasing trend until the last decade. It rises from 0.64 cents/kWh in 2020 to 1.06 and 1.30 cents/kWh by 2040 in BAU and sustainable schemes, respectively, decreasing slightly. Putting renewable and nuclear technologies on the map, which have generally higher O&M costs, justifies that increase in the sustainable plan. In BAU, decommissioning the existing steam power plants with small O&M costs is one reason for that increasing trajectory. In addition, concerning the total cost, the model suggests advanced combined cycle technologies rather than the conventional ones because the advanced systems work in higher conversion efficiency, even though they necessitate more maintenance costs.

Levelised cost of electricity (LCOE)

The BAU, by and large, leads to favorable economics in the sense of LCOE. The indicator lies within the range of 6.21 to 6.49 cents/kWh for BAU, while within 6.24 and 6.57 in the sustainable plan. Increasing O&M cost in midterm causes a higher level of LCOE for both schemes compared to the 2020 level. From 2035 to 2040, the fuel cost decline, coupled with stabilized investment cost, brings a sensible LCOE decrease in BAU. A smother decline is observed in the sustainable plan due to the high investment cost of deploying clean technologies. As a result of the combined cycle rising share, and subsequently, fuel expense soaring in the last periods, LCOE turns to an increasing trend and sits at 6.49 and 6.57 cents/kWh in BAU and sustainable schemes, respectively.

Fuel price sensitivity

As a function of fuel price and LCOE, fuel price sensitivity is more affected by the former and proceeds the same trend of that. Before 2030, the meter stays almost flat, around 50% in the two schemes. After that, it behaves like an inverted bell curve, falls to 42% and 27% by 2045 in BAU and sustainable plan, respectively, and rises again up to 46% in BAU and 32% in the sustainable plan. Sensitivity to fuel price dwindles in sustainable development following the diffusion of renewable technologies.

Economic dispatchability

As the ratio of investment cost to LCOE, economic dispatchability shows a path like the numerator because of more severe fluctuations. After passing a relatively smooth line during the first decade, it grows from 37% to 42% in BAU and 53% in the sustainable plan. Accordingly, at its maximum difference occurred in 2045, economic dispatchability in the sustainable plan is 13% more than the BAU. With a decline in the ending years, the indicator sits at 41% and 48% in BAU and sustainable plan, respectively.

Construction time

The average construction time in both plans continuously follows a decreasing pattern, so from the current 4.85 years diminishes to 3.41 and 2.70 years in 2050 for BAU and sustainable schemes, respectively. Synchronous with the intense penetration of clean technologies, this index faces a decreasing trend in the sustainable plan. Although nuclear units need longer time to be built, the sustainable plan is more affected by solar and wind technologies, which need shorter times to start up.

Capacity factor

From the capacity factor standpoint, the BAU is more reliable than sustainable expansion. At the end of the planning projection, that indicator in BAU shows a decrease as negligible as 4% compared to 2020. In the sustainable power mix, however, only 38% of the 2050 on-hand capacity contributes to the electricity supply. Pursuing the substitution of baseload combined cycle with variable solar and wind sources triggers that result.

Fig. 7. The trends of techno-economic indicators in BAU and sustainable schemes (per unit of generation).

4.2.2. Annual costs

Fig. 8 represents per year imposed investment, O&M, and fuel costs. Versus fuel cost, the annual investment and O&M cost continually increase over time, where a higher growth speed in the sustainable plan is observed. Investment cost in sustainable design increases by a 4.5% average annual rate, rising from the current 8.2 to about $30.5 billion in 2050. That rate accounts for 3.7% in BAU. The demand push along with penetration of nuclear power and renewables, which in midterm still require more capital costs than fossil fuel plants, are the reasons for that increasing trend.

With a similar pattern, O&M annual cost rises from $2.15 billion in the base year to 8.66 and 11.8 in BAU and sustainable plans, respectively, denoting 4.7% and 5.8% average growth rates. The fuel cost pattern contrasts with the priors, wherein the sustainable plan presents lower levels of annual expense. Although in BAU a constant yearly growth is observed in fuel spending, in the sustainable generation, thanks to renewables deployment, a substantial decrease takes place within 2035 to 2040. However, penetrating fossil fuel power plants in the last periods turns the trend to the upside. Following this pattern, $10.7 billion fuel cost in the present-day grows to $20.5 billion in 2050.

Fig. 8. Total annual costs of electricity supply in BAU and sustainable schemes.

4.2.3. Environmental indicators

The performance of the two plans in terms of environmental criteria is shown in Fig. 9.

Water consumption

Regardless of some temporal fluctuations, a continuous improvement in water consumption is seen in both plans, but sustainable design leads to a better result. The required water for one megawatt-hour of electricity is about 640 gallons in the current generation mix. The reduction to 324 and 282 gallons is expected for BAU and sustainable plan, representing a 46% and 56% decrease relative to 2020. Phasing out the existing steam power plants of most water-intensive technologies is the main reason behind the two plans' decreasing pattern. Although more nuclear power in the sustainable plan should result in more water consumption, the high growth rate of solar and wind power makes a balance so that the decreasing trend is kept during the planning horizon.

Acidification

Until 2030, per MWh SO_2 emissions, sink below 277 gr in BAU. In fact, no substantial increase is observed. The reason is that by that time, no extensive change in the share of fossil fuel technologies, which have approximately the same level of acidification potential, would be occurred. In the long-term, however, the acidification potential reduces to 223 gr/MWh as a result of decreasing share of fossil fuel technologies. A remarkable decrease is observed in sustainable plan, such that the indicator diminishes to 136 gSO_2/MWh, which is 48% lower than that of the present. Alternative options, including nuclear, solar PV, solar thermal, and wind turbine, all in comparison with fossil fuel power plants have lower levels of acid gas emissions. Putting those clean technologies into play explains the considerable drop.

Land use

Both schemes tend to occupy more land than the current, however, installing coal-fired power stations makes the BAU more land-intensive. The current per megawatt-hour land occupation is about 3.83 m^2. Over the coming decades, it is projected to increase and reach around 5.78 and 6.19 m^2 in 2050 in sustainable and BAU plans, denoting a 51% and 62% increase, respectively. The conventional steam power plant, gas turbine, and combined cycle are compacted in terms of facilities so that they need only 4% of the land needed in solar systems to produce the same amount of electricity. Accordingly, moving a bit towards solar technologies, as happens especially in sustainable expansion, causes a considerable increase in land demand.

Global warming

Thanks to clean technologies utilization and efficiency improvement, both designs achieve a fast reduction in global warming potential by 2045. Yet, the trend turns to the upside during the last period due to increased combined cycle share. From an estimated 443 gCO_2/MWh in 2020, emissions reduce to 261 gr in BAU and 138 gr in the sustainable plan at their minimum levels, which show a sizeable 41% and 69% decline, respectively. Through pursuing sustainable development, CO_2 emissions would lie at 150 gCO_2/kWh at the endpoint of the planning horizon, which accounts for one-third of the current level.

Fig. 9. The trends of environmental indicators in BAU and sustainable schemes expressed per unit of generation.

4.2.4. Annual environmental performance

Fig. 10 provides the annual operation of the environmental index. In the medium- to long-run, there are some time frames wherein yearly SO_2 and CO_2 emissions reduce. However, the required water and land constantly increase year by year. If the present arrangement continues, the acidification potential will rise from 88 to 212-kilo tonnes SO_2 per year. The sustainable supply can moderate this outcome by up to 83-kilo tonnes reduction in annual SO_2 emissions.

Although the electricity demand is progressively rising, even in the BAU, there would be no substantial increase in yearly CO_2 emissions until the last decade. The emissions sink below 191 Mt by 2040 but increase to 270 Mt in 2050. In the sustainable expansion, a 39% decrease is observed compared to the present level, reaching 91 Mt in 2040. In 2050, the amount of emissions in the sustainable plan is almost the same level as 2020, but 45% lower than that of BAU.

Even though per MWh water requirement is decreasing over time, electricity generation expands at such an accelerating rate that the annual water need is persistently mounting going forward in both plans, a bit more in the BAU. The annual demanded water rises less than 44% during the 30-year timeframe and reduces from 214 billion gallons in the base year to a range between 272 and 307 billion gallons in 2050, depending on the plan.

Land occupation also follows an increasing trend over time regardless of the expansion plan. With incremental growth, the area needed to satisfy the demand surpasses fourfold and grows from 1288 million m^2 in 2020 to 5451 and 5867 million m^2 in 2050 in sustainable plan and BAU. At the horizon of 2050, the total land occupation in the sustainable scheme is 7.01% lower than that of BAU.

Fig. 10. Total annual environmental impacts of electricity supply in BAU and sustainable schemes.

4.2.5. Social indicators

Fig. 11 displays the performance of the BAU and sustainable scheme regarding social perspectives.

Job creation

Typically, all the alternative technologies have higher job creation potential. Consequently, jobs associated with both expansion plans tend to rise. At present, the index is around 133 person-yrs for each terawatt hour of electricity. In long-run, job creation per unit of electricity in the sustainable plan is higher than that of BAU. The indicator is expected to grow less than 47% by 2050 in BAU and 83% in the sustainable plan, reaching 195 and 244 person-yrs.

Human toxicity potential

Human toxicity potential increases over the next two decades in both plans and then stabilizes in the sustainable scheme and turns to a decreasing trajectory in BAU. The current power supply mix causes 3.77 gr 1,4.DCBeq per kWh output. In line with the increase in the share of wind, solar thermal, and more importantly, solar photovoltaic, which have higher toxicity potential relative to fossil fuels (except for coal), the performance in the sustainable design deteriorates, reaching 7.69 gr 1,4.DCBeq/kWh in 2050. BAU is more harmful than sustainable development in terms of toxicity potential, mainly due to higher dependency on coal-fired power stations that are by far the worst option concerning toxic gases and vapors. The index in BAU is around 9.49 gr at the horizon 2050, 23% more than that of the sustainable scheme.

Fossil fuel consumption

Fossil fuel consumption decreases in both scenarios, falling from the present-day value of 7.1 MJ/MWh to 4.2 to 4.7 in BAU and 2.7 to 2.9 in the sustainable plan in the last decade. This implies that the required fossil fuel-sourced energy to produce a unit of electricity can be around 40% of the current amount if sustainability is pursued. The expected cost reduction of renewables is so high that they would be a part of the solution even in an economic-focused aspect. This results in less dependency on fossil fuel not only in the sustainable plan but also in BAU.

Diversification

Supply mix diversification based on the Shannon-Wiener measure [65] sinks below 1.54 in the sustainable scheme and shows fluctuations in a range of 1.51 and 1.65 in BAU within the first decade. Within the next five years, it decreases to 1.42 in the BAU and increases to 1.69 in the sustainable scheme. In the remaining periods, the sustainable design presents better performance regarding diversification. The higher level of the index in BAU during the first decade is due to contributing coal power plants to the generation. After 2030, an enormous increase in the share of solar systems and wind turbines justifies the higher levels of diversification in sustainable strategy. In 2050, the index in the sustainable plan shows a 13% improvement compared to the base year and almost the same amount of superiority relative to the BAU. The decreasing trend prior to 2035 lies in decommissioning steam power. However, between 2035 and 2040, an enormous increase in the share of solar systems, wind turbines, and then nuclear power leads to a jump in the index.

Fig. 11. The trends of social indicators in BAU and sustainable schemes expressed per unit of generation.

4.2.6. Annual social performance

Fig. 12 presents the annual performance in social criteria. The total employment in the current supply system is estimated to be over 45 thousand person-years. In both plans, job creation is steadily increasing, so that the indicator reaches 185 thousand person-years in BAU and 56 thousand more in the sustainable scheme. Accordingly, based on sustainable development, the total number of jobs on the horizon 2050 would be five times surpassing the current. Aligned with the continuous increase in demand, the penetration of solar PV, which employs more than sevenfold staff compared to fossil fuel technologies, is the main reason for that increasing trend. Replacing the combined cycle mainly by wind turbine justifies the higher level of the indicator in the sustainable plan.

In all periods, the BAU's human toxicity potential experiences higher levels than that of the sustainable scheme. In 2050, there is a difference as high as 1.5 Mt between the two plans. By an average annual growth rate of over 6.2%, the sustainable plan's toxicity increases from 1.2 to about 7.2 Mt 1,4.DCBeq within the period 2020 to 2050.

Fossil fuel energy consumption per unit of electricity decreases in such an accelerated transition that the annual usage declines 27% by 2040 in the sustainable plan. As a result of combined cycle diffusion, the indicator turns increasing during the last decade. Nevertheless, the total yearly energy requirement at the end of the planning period is only 11% greater than the present. In the BAU, huge dependency on fossil fuels still exists so that in 2050, close to 4480 PJ energy is sourced from fossil fuels, which is 67% more than the sustainable plan.

Fig. 12. Total annual social impacts of electricity supply in BAU and sustainable schemes.

5. Discussion

This section aims to discuss the results and determine the validity of the proposed methodology. For that purpose, three extreme scenario variants are first defined to examine the function of weights in the model. Then, the results of the sustainable plan are compared with some similar previous works. Finally, the importance of short-term variations of the variable renewable energy sources is discussed.

5.1. Model validation

Extreme scenarios help to determine whether the model’s output is reasonable. Among the considered indicators, the maximum possible weight (100%) is dedicated to LCOE in the first variant (S_{LCOE}). The other two variants are moved towards environmental sustainability. This is done by allocating a weight of 80% to global warming in the second variant (S_{CO2}) and to water consumption in the third variant (S_{Water}). The remaining 20% still belongs to LOCE in both variants.

Fig. 13 shows the generation share of solar systems, wind turbine, and other clean technologies. Variant S_{LCOE} is close to the BAU in terms of renewables and clean technologies contribution. This was predictable since the two schemes merely matter the costs of the system. Although solar PV is the most favorable renewable in the short-term, wind turbine share increases at a faster pace and gets the first priority among clean power plants in the long-term. Expectedly, variant S_{CO2} has the highest share of clean sources where besides solar and wind, nuclear and hydropower largely contribute to electricity supply. When the emphasis is put on water consumption, it is observed in S_{water} that wind turbine by far becomes the most favorable renewable since its water usage is economically fewest.

Fig. 13. Generation share of clean technologies in extreme scenarios.

To take further insights about the methodology and results, three related previous studies are selected for comparison. Aryanpur and Shafiei [59] analyzed the impact of renewable sources deployment on Iran's power sector. They used the MESSAGE model to optimize capacity expansion. Fossil fuel price was increased, and the carbon tax was imposed in deployment scenarios. The most important difference of that research with the current study from the methodological point of view is that instead of using an energy system tool, this paper has developed its own mathematical model, which makes it flexible for further development. Moreover, the considered research only regarded cost while making the decision. The results of the two studies, however, support each other. Aryanpur and Shafiei [59] concluded that the combined cycle is the most promising technology. Among renewables, wind turbine and solar PV have been recognized as the first and second priorities. This study also suggests the same, but it puts more emphasis on renewables. The reason is twofold. One is due to decreasing capital cost of wind and solar technologies within the last five years and the expectation for a further decline in the midterm. Another reason is that considering sustainability criteria pushes decisions towards more renewables' diffusion, as they are more compatible with sustainability measures.

Santoyo-Castelazo and Azapagic [51] assessed Mexico's power generation options in terms of life-cycle sustainability. In their method, the evaluation of generation mixes as scenarios was accomplished after configuring the future energy supply. Thus, there was a limitation on the exploration of numerous generation portfolios. This is a source of difference with the proposed methodology, where scenario ranking is automatically done within the process. The other development in this study is utilizing an optimization model to characterize the energy system instead of predetermining technologies' contribution. The results showed that when the equal weighting strategy is followed, a green scenario in which the share of gas and coal are substantially decreased in favor of the wind, solar thermal, and solar PV is the most attractive option. However, that study criticized equal weighting as the selected scenario had some critical social aspects. Paying more attention to stockholders' opinions led to less wind and solar contribution but increased the share of biomass, nuclear, and hydropower. Except for some differences that are related to local potential, there are some general lessons common in the two studies. In both studies, when sustainability is concerned, a more distributed energy portfolio is suggested. Moreover, solar and wind are recommended to have a moderate to large share depending on the country's resources and infrastructure.

Atilgan and Azapagic [66] identified sustainable options for Turkey's future electricity generation. They defined different scenarios in which the future mixes were changed. They then evaluated scenarios according to a set of sustainability indicators. They ranked scenarios through an MCDM method based on their performance in the indicators. They didn't deal with stakeholders regarding sustainability preferences. Moreover, they assumed the generation mixes only based on the scenario's assumptions. Both that paper and the current study conclude that clean technologies scenarios outperform fossil fuels scenarios from the overall sustainability aspect. The increasing trend of job creation and decreasing trend of per unit acidification in different scenarios are also among similarities in the results. However, that research predicted a higher level of investment costs in renewable-based scenarios in comparison with the current study. This discrepancy stems from the higher ratio of clean technologies. In the case of Iran, wind and solar totally would contribute less than 50% by 2050, but capital-intensive scenarios for Turkey would supply near 80% of electricity from renewables.

The discussion above affirms that the proposed methodology illustrates the future electricity generation reasonably. The results are in accordance with the previous works, although some differences exist because of different input data and assumptions. In summary, it can be said that the main strength of the proposed framework is its accuracy. Some previous studies simply use assumed future generation configurations and then try to find the best one [66]. This paper, however, develops a programming model to characterize the future mixes. Some other works either do not care about experts' opinions [67] or consider them at the final stage to sort a limited number of scenarios [68]. This paper, however, applies the expert's preferences iteratively within the process.

5.2. The role of storage and time resolution

The massive penetration of renewable energies has a substantial impact on the operation of the power system. In this system, the role of storage technologies as a source of flexibility would become crucial [69]. This especially is highlighted when the focus is on the operational plan, including very short-term intervals rather than long-term foresight drawn by strategic planning. Thus, increasing time resolution is essential to accommodate the intermittency of renewable energy sources. As the present work does not explicitly model the variations, the long-term results are compared with similar studies to know the validity of the results. More specifically, the section explores whether the existing studies that projected Iran's power supply in higher temporal resolution and the presence of storage technologies support the prospect mix proposed by this paper.

Aghahosseini et al. [70] examined the possibility of 100% renewable electricity for Iran by 2030. They concluded that a full renewable-based power system is reliable, low-cost for Iran. Among the total 180 GW capacity in 2030, above 70% belonged to wind turbine and solar PV. The main point is that the suggested capacity for the storage was only 5 GW. The reason mentioned was that the country has a high availability of renewable sources which can produce electricity all year round.

Another study done by Ghorbani et al. [71] again exploring transition pathways towards a fully renewable source power in Iran shows that the storage technologies should be added to the system after 2030 when the share of variable renewables reaches about 60% of total generation. It is noticeable that in more recent research, Ghorbani et al. [58] concluded that under the best policy scenario, storage technologies would come into effect once variable renewables dominate the market share (over 90% of the total generation).

The share of variable renewables in the current study never exceeds 50%. In comparison with the previous studies, this amount can be considered low enough to express that neglecting hourly time resolution and storage technologies may not substantially affect the long-term picture of the portfolio. Moreover, at the end of the planning horizon, fast response gas turbines and hydropower plants still play a significant role, reaching together about 10% of total installed capacity. Nevertheless, increasing time resolution and taking storage technologies into account would be helpful to ensure that blackout will not occur in all time slices. The advantage of the proposed model is that it consists of linear terms with continuous variables. This feature makes the model easy in terms of computational complexity, so provides a suitable foundation for future detailed models incorporating higher temporal resolution. By considering charging and discharging power respectively in the right- and left-hand sides of Eq. (A.10), satisfying demand can be guaranteed.

6. Conclusions

This study developed an integrated simulation-optimization framework to address sustainability in energy transition pathways. Taking advantage of an artificial intelligence technique, the framework brought an EA into play to search for future electricity supply configurations. The algorithm removed the limitation of the existing optimization-based methodologies in dealing with numerous prospect configurations. The EA provided the means to explore normative scenarios and, in this way, played the role of a simulation model, making possible backcasting. Within the EA, an LP model was set to formulate dynamic interactions in the energy system. The model was utilized to find the best pathway towards each scenario, shaping the forecasting-backcasting outline. In order to evaluate scenarios in terms of overall sustainability, the VIKOR, as an MCDM tool, was involved inside the process. ANP method was also applied to determine the preference importance of sustainability criteria, taking interdependencies into account in an open dialogue with experts. The methodology was employed to examine how harnessing low-carbon sources in Iran would affect the supply sector arrangement.

The results show that onshore wind turbines and solar PVs should be put on the map even in the BAU scheme. In the sustainable transition, however, they will play a more significant role. At the horizon of 2050, near 40% of electricity would come from these two sources. Besides, the solar thermal plant is another source that distinct the sustainable plan from BAU. These variable renewable energy technologies would satisfy around 48% of the total demand.

The findings reveal that moving towards renewables would lead to some deterioration in economic outlooks but improve most of the environmental and social indicators. As a result of an increase in investment and O&M costs, the sustainable plan would raise LCOE up to 6%. Lower fuel costs in the sustainable scenario balance total costs and prevent a substantial increase in electricity per-unit cost. Putting wind turbine, solar PV, and solar thermal into operation leads to a persistent decrease in water consumption, fossil fuel consumption, and subsequently, CO_2 emissions in both plans. Sustainable development also triggers a significant decline in SO_2 emissions and continuous growth in job creation. Both scenarios regarding land requirements and human toxicity potential follow a deteriorating trajectory, while the sustainable plan moderates the trends. All in all, the trends show that some advances would stop or turn to the upside within the last decade of planning due to the limitation on renewables exploitation. This denotes that if the country desires to improve socio-environmental practices long-term, paving the way for more renewable technologies should be coupled with energy efficiency and demand-side management.

Future works could use many-objective EAs to take sustainability aspects as objective functions [72], and robust optimization approaches to cope with different types of uncertainty [73]. The developed model accounts for the network's loss as an exogenous parameter. It can be extended to analyze the effects of grid constraints. This study used plant-level data (like [74]). Although a comparison showed that the overall future picture of electricity supply would not change if a life cycle approach is followed, the detailed possible differences could be revealed in future studies. Finally, aggregated spatial and temporal details limits this analysis. Future research might investigate higher spatio-temporal resolution to better incorporate the intermittency of renewable energy sources and demand fluctuations [75].

Appendix A. The linear programming model for power supply optimization

This section provides an LP model for optimizing the RES. The following notations are used to formulate the model.

Sets:

T	Period
I	Power generation technology (I_c: centralized, I_d: distributed, I_f: non-renewable, I_r: flexible)
J	Fuel (J_i: fuel types used in technology i)

Parameters:

cc	Capital cost
pc	Decommissioning cost
fc	Fuel price
xc, vc	Fixed and variable O&M costs
tc, dc	Transmission and distribution costs
ic, ec	Import cost and export price
r	Discount rate
d	Electricity demand
lt	Technology lifespan
ct	Installation time
s	Self-consumption percentage
η	Technology efficiency
l	Load factor
h	Heat value
fu	Maximum available fuel
δ, γ	Transmission and distribution losses
le, ue	Minimum and maximum amount of existing capacity
ln, un	Minimum and maximum amount of new installed capacity
lp, up	Minimum and maximum amount of total available capacity
$\varepsilon', \varepsilon$	Minimum and maximum share in generation
α', α	Minimum and maximum share of import
β', β	Minimum and maximum share of export
θ', θ	Minimum and maximum share of fuel

Variables:

C, C^{New}, C^{Ext}	Available capacity (total, newly installed, existing)
G, G^{New}, G^{Ext}	Electricity generation (total, from newly installed capacity, from existing capacity)
P	Capacity being installed
F	Required fuel
Dr, No	Distribution network input and output
Im, Ex	Imported and exported electricity
Tr	Transmission grid input

The objective function presented in Eq. (A.1) attempts to minimize the total discounted cost of the energy system.

$$Min \sum_{t \in T} \frac{TC_t}{(1+r)^t} \tag{A.1}$$

where

$$TC_t = \left[\sum_{i\in I}(cc_{it}+pc_{it})P_{it}\right]_{\text{Investment cost}} + \left[\sum_{i\in I} xc_{it}C_{it} + \sum_{i\in I} vc_{it}G_{it}\right]_{\text{O\&M cost}} +$$
$$\left[\sum_{j\in J}\sum_{i\in I_f} fc_{jt}F_{\text{ijt}}\right]_{\text{Fuel cost}} + \left[tc_t Tr_t + dc_t Dr_t\right]_{\text{Grid cost}} + \left[ic_t Im_t - ec_t Ex_t\right]_{\text{Tradingcost}} \tag{A.2}$$

The objective function is subject to the following constraints. Eqs. (A.3)-(A.6) describe the capacity limitations. Eq. (A.3) associates the available new installed capacity with the time of installation. Eqs. (A.4)-(A.6) impose upper and lower bounds for the capacity of existing and newly installed plants.

$$C_{it}^{New} = \sum_{t'=\max\{t-ct_i-lt_i+1,1\}}^{t-ct_i} P_{it'} \quad \forall t > ct_i \quad \forall i \in I \tag{A.3}$$

$$ln_{it} \le P_{it} \le un_{it} \quad \forall i \in I \quad \forall t \in T \tag{A.4}$$

$$le_{it} \le C_{it}^{Ext} \le ue_{it} \quad \forall t \in T \quad \forall i \in I \tag{A.5}$$

$$lp_{it} \le C_{it} \le up_{it} \quad \forall t \in T \quad \forall i \in I \tag{A.6}$$

Eqs. (A.7) and (A.8) define the power generation constraints resulting from capacity limitation or maximum possible share of each technology. Eq. (A.9) denotes that the generation share of flexible (fast response) technologies should exceed a predetermined level for considering temporal demand fluctuations.

$$G_{it} \le 8760\, l_i\, (1\text{-}s_i)\left(C_{it}^{New} + C_{it}^{Ext}\right) \quad \forall t \in T \quad \forall i \in I \tag{A.7}$$

$$G_{i,t} \le \varepsilon_{i,t} \sum_{i\in I} G_{i,t} \quad \forall t \in T \quad \forall i \in I \tag{A.8}$$

$$\sum_{i\in I_r} G_{i,t} \ge \varepsilon'_t \sum_{i\in I} G_{i,t} \quad \forall t \in T \tag{A.9}$$

Eqs. (A.10)-(A.12) guarantee electricity demand satisfaction either by grit output, decentralized generation, or import.

$$No_t + \sum_{i\in I_d} G_{it} = d_t \quad \forall t \in T \tag{A.10}$$

$$(1-\delta_t)Dr_t = No_t \quad \forall t \in T \tag{A.11}$$

$$Dr_t = (1-\gamma_t)Tr_t - (1-\gamma_t)^{-1}Ex_t \quad \forall t \in T \tag{A.12}$$

Eq. (A.13) calculates fuel requirements for electricity generation. Eqs. (A.14) and (A.15) control fuel consumption and contribution.

$$3.6\times10^{3}G_{it} \le \sum_{j\in J_i} F_{ijt} h_j \eta_i \quad \forall t \in T \quad \forall i \in I_f \tag{A.13}$$

$$\sum_{i\in I_f} F_{ijt} \le fu_{jt} \quad \forall j \in J \quad \forall t \in T \tag{A.14}$$

$$\theta'_{jt} \sum_{j'\in J} \sum_{i\in I_f} l_{j'} F_{ij't} \le l_j \sum_{i\in I_f} F_{ijt} \le \theta_{jt} \sum_{j'\in J} \sum_{i\in I_f} l_{j'} F_{ij't} \quad \forall j \in J \quad \forall t \in T \tag{A.15}$$

Eq. (A.16) computes the amount of import based on the total generation and transmission input. Eqs. (A.17) and (A.18) restrict trading volume as a fraction of generation.

$$Im_t = Tr_t - \sum_{i\in I_c} G_{it} \quad \forall t \in T \tag{A.16}$$

$$\alpha'_t \sum_{i\in I} G_{it} \le Im_t \le \alpha_t \sum_{i\in I} G_{it} \quad \forall t \in T \tag{A.17}$$

$$\beta'_t \sum_{i\in I} G_{it} \le Ex_t \le \beta_t \sum_{i\in I} G_{it} \quad \forall t \in T \tag{A.18}$$

Appendix B. The sustainability parameters of power generation technologies

The sustainability parameters of the considered technologies are given in Table B1.

Table B1. Techno-economic, environmental, and social parameters of power generation technologies [59] [11] [57] [76] [61] [77] [78] [79] [80] [81] [51] [82] [55] [83].

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Figures:

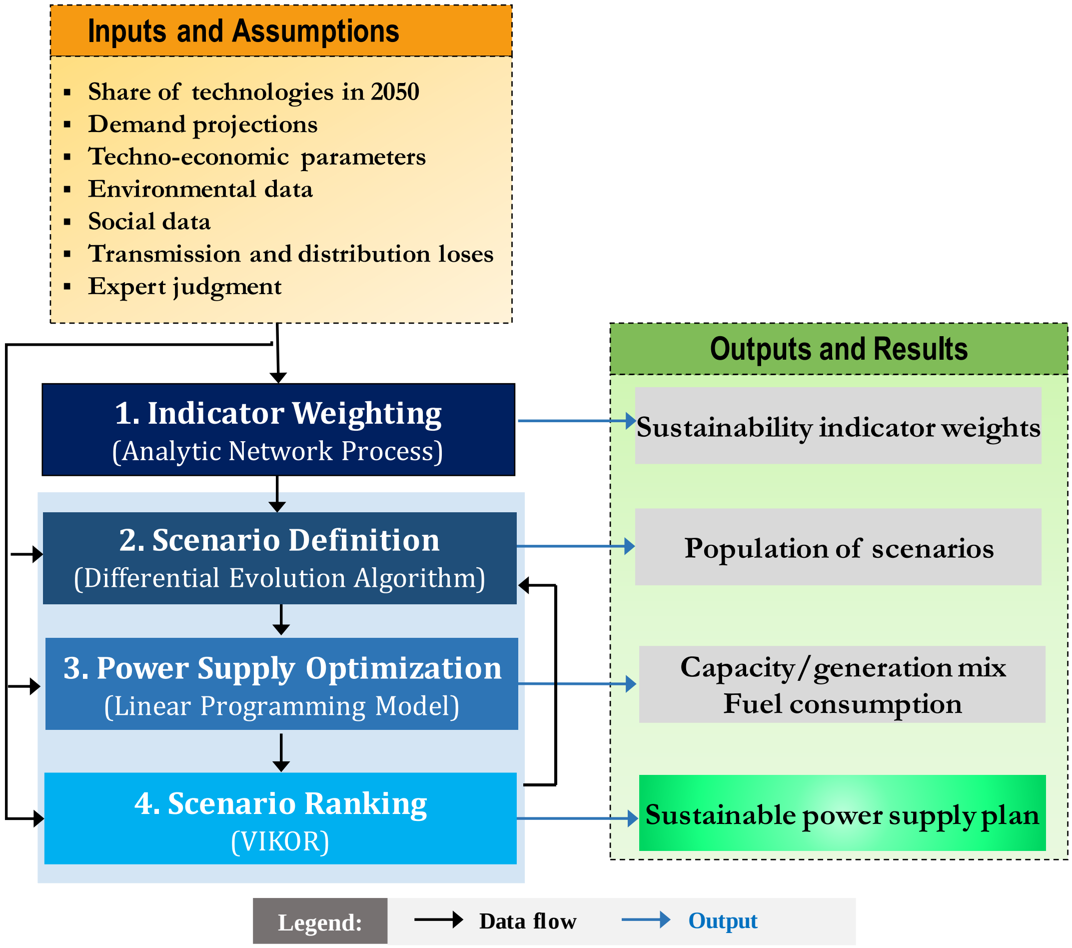

Fig. 1. The schematic representation of the proposed simulation-optimization framework.

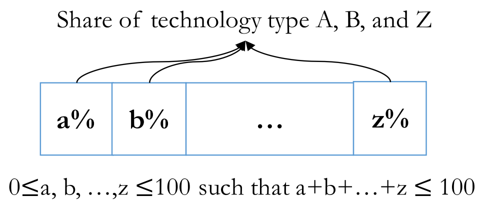

Fig. 2. Solution representation scheme in the designed DE algorithm.

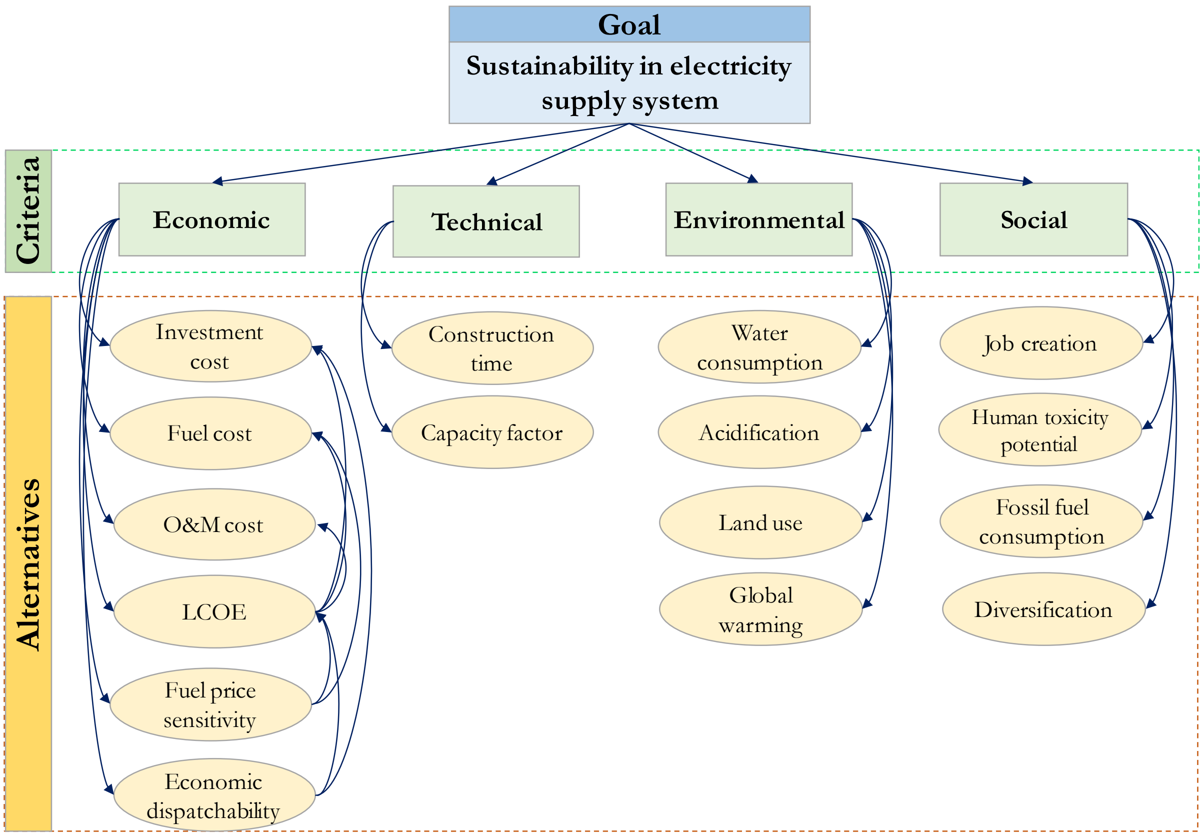

Fig. 3. Sustainability indicators and their relationship network in the ANP method.

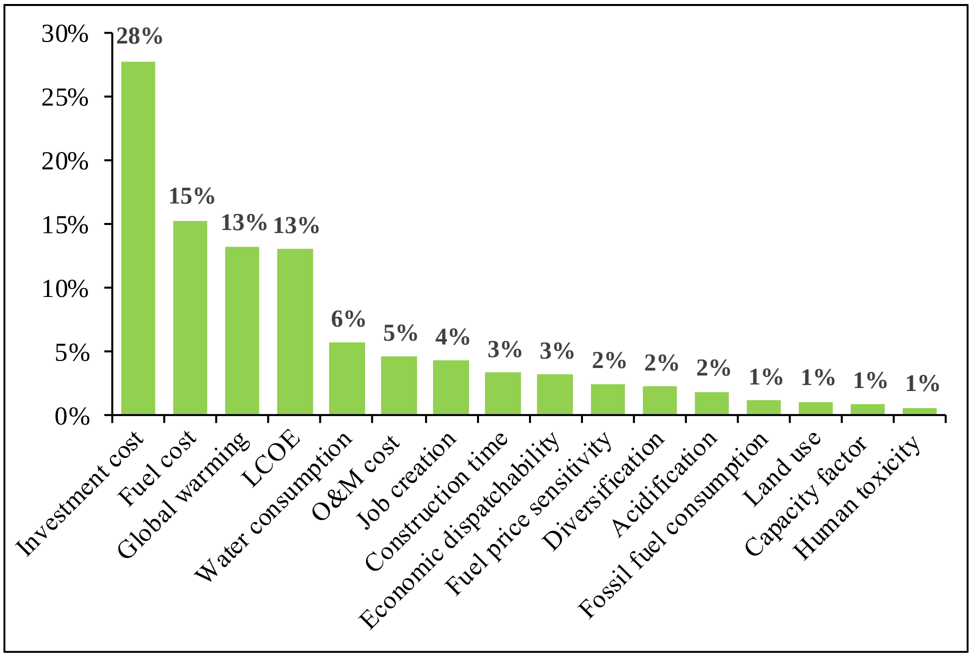

Fig. 4. Sustainability indicators' weights for the case of Iran.

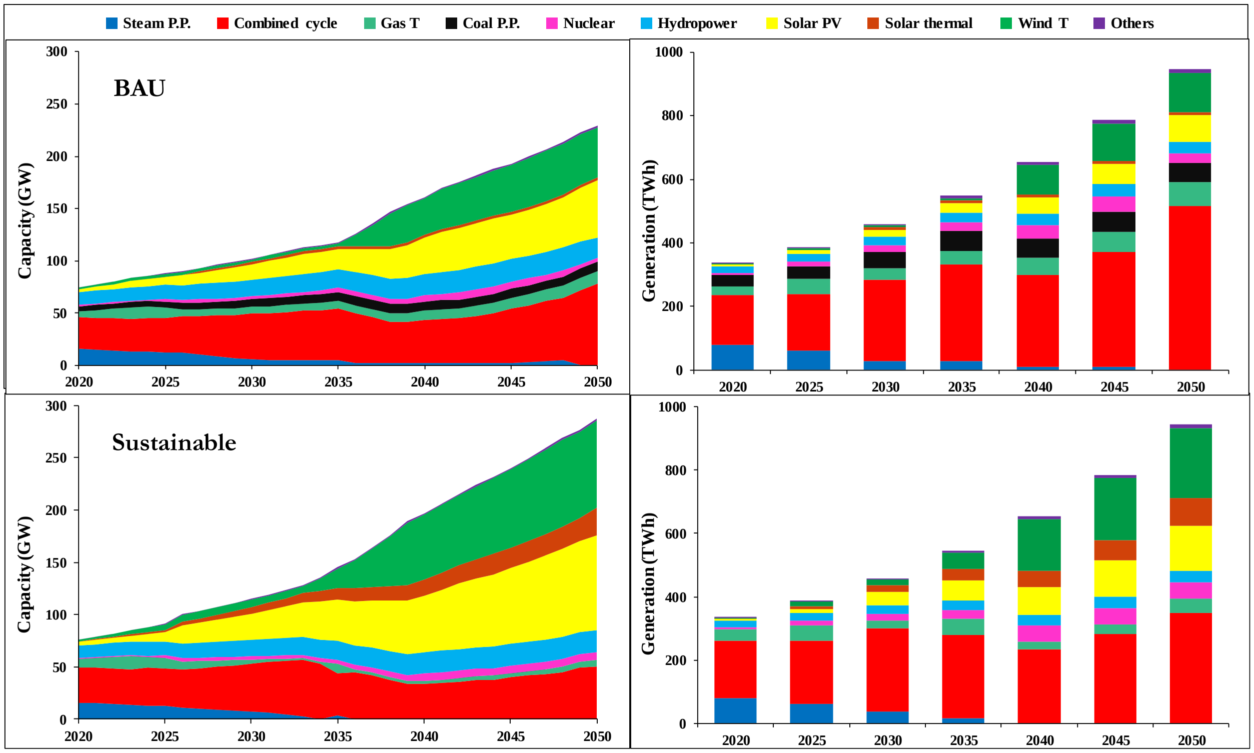

Fig. 5. Capacity and generation pathways in the BAU and sustainable schemes up to 2050.

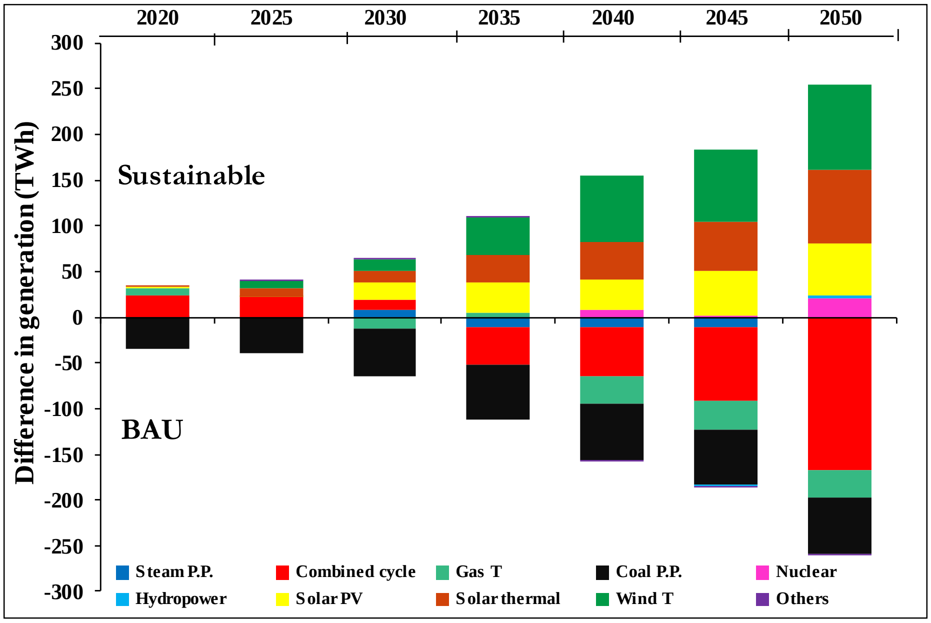

Fig. 6. Change in electricity generation source due to development sch

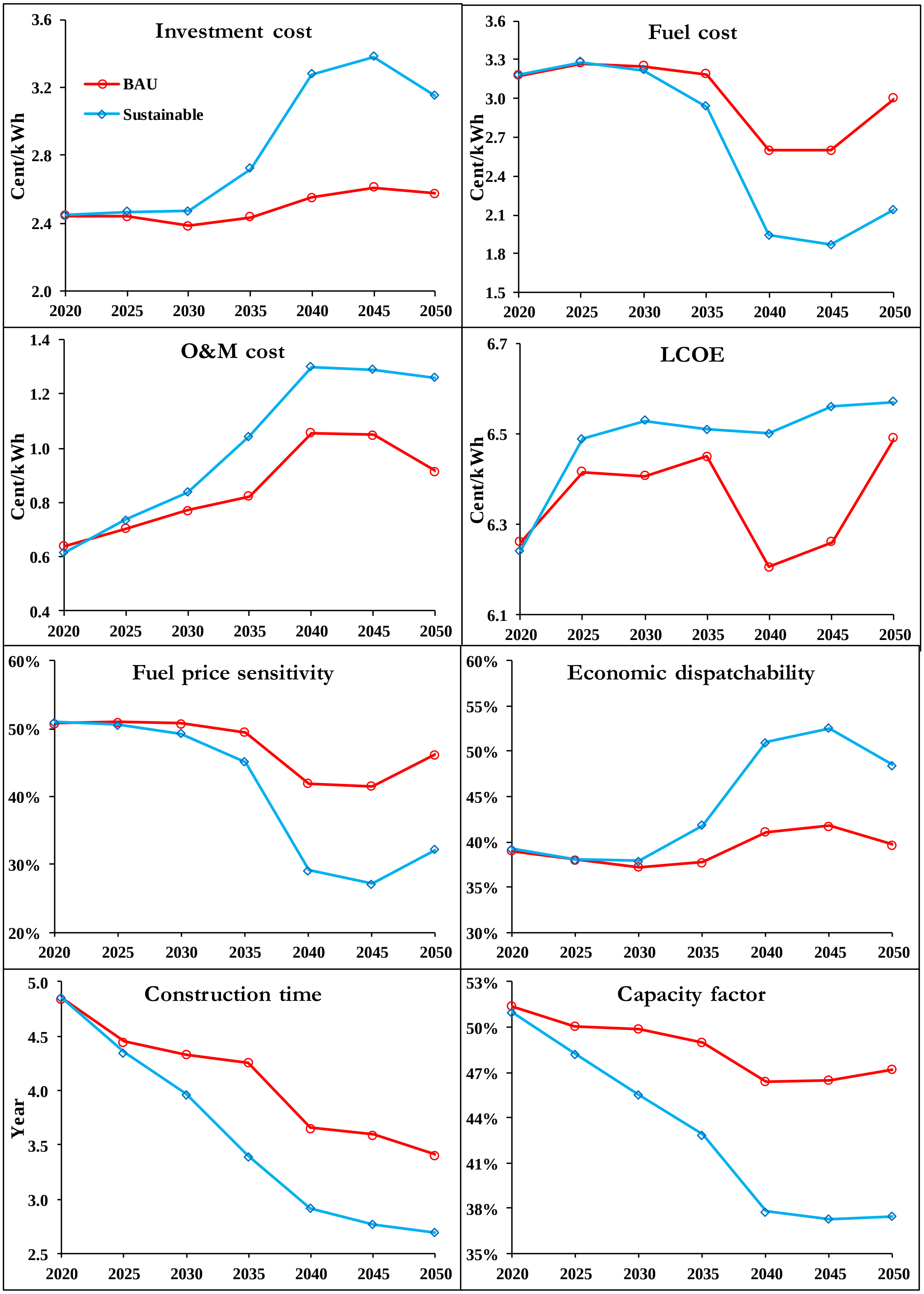

Fig. 7. The trends of techno-economic indicators in BAU and sustainable schemes expressed per unit of generation

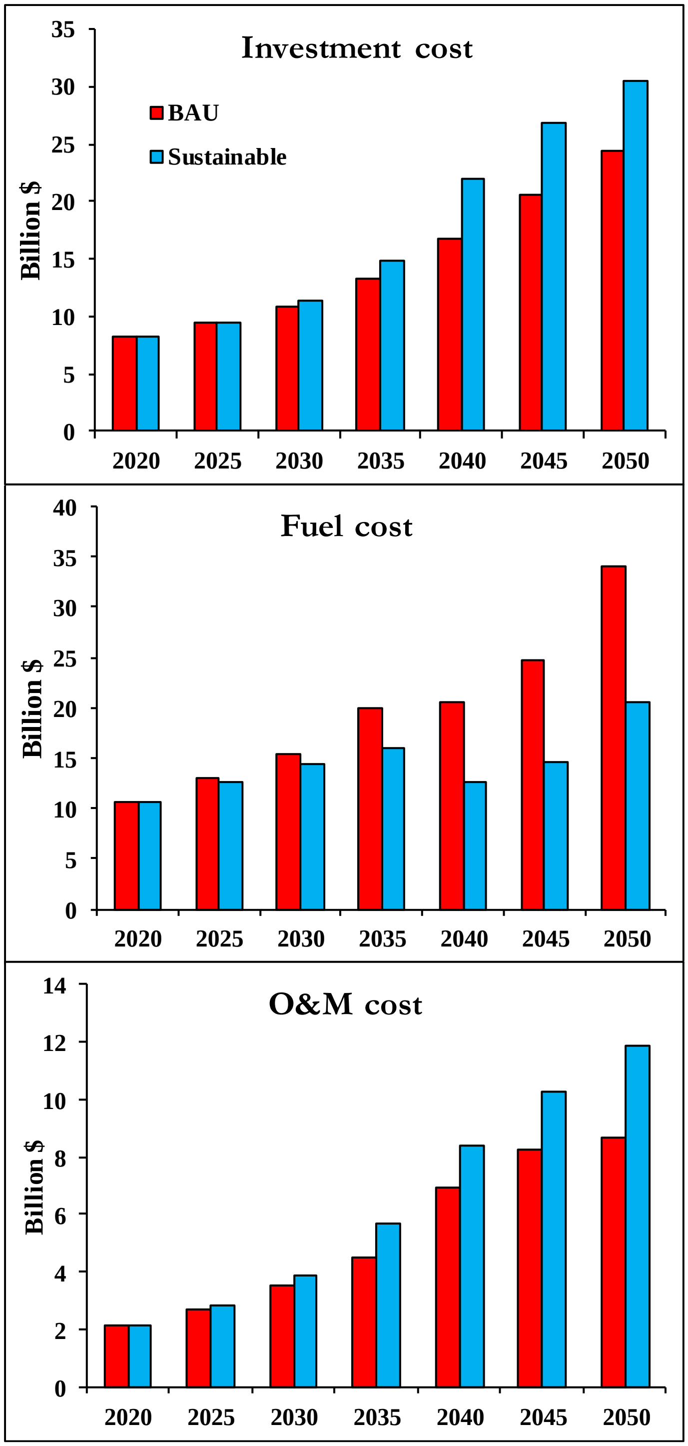

Fig. 8. Total annual costs of electricity supply in BAU and sustainable schemes.

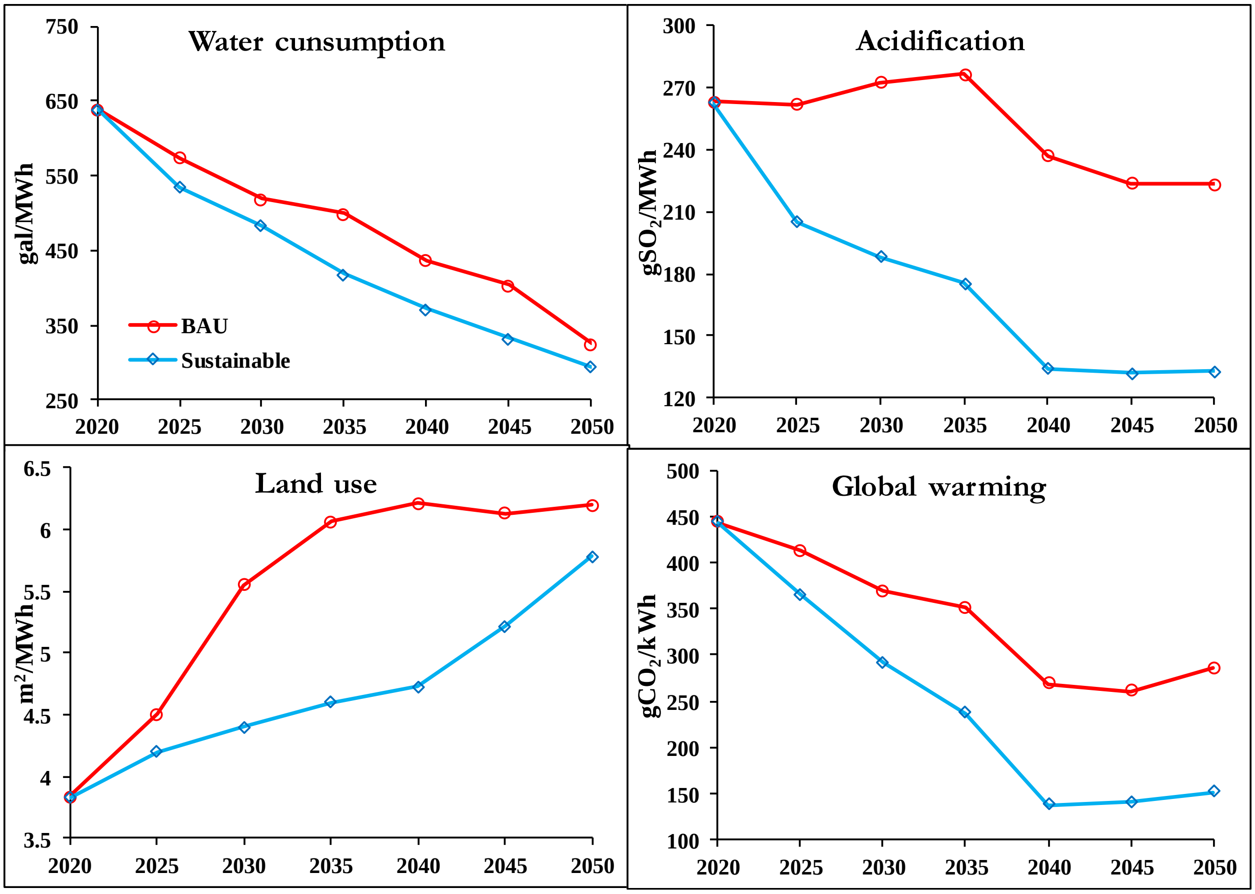

Fig. 9. The trends of environmental indicators in BAU and sustainable schemes expressed per unit of generation.

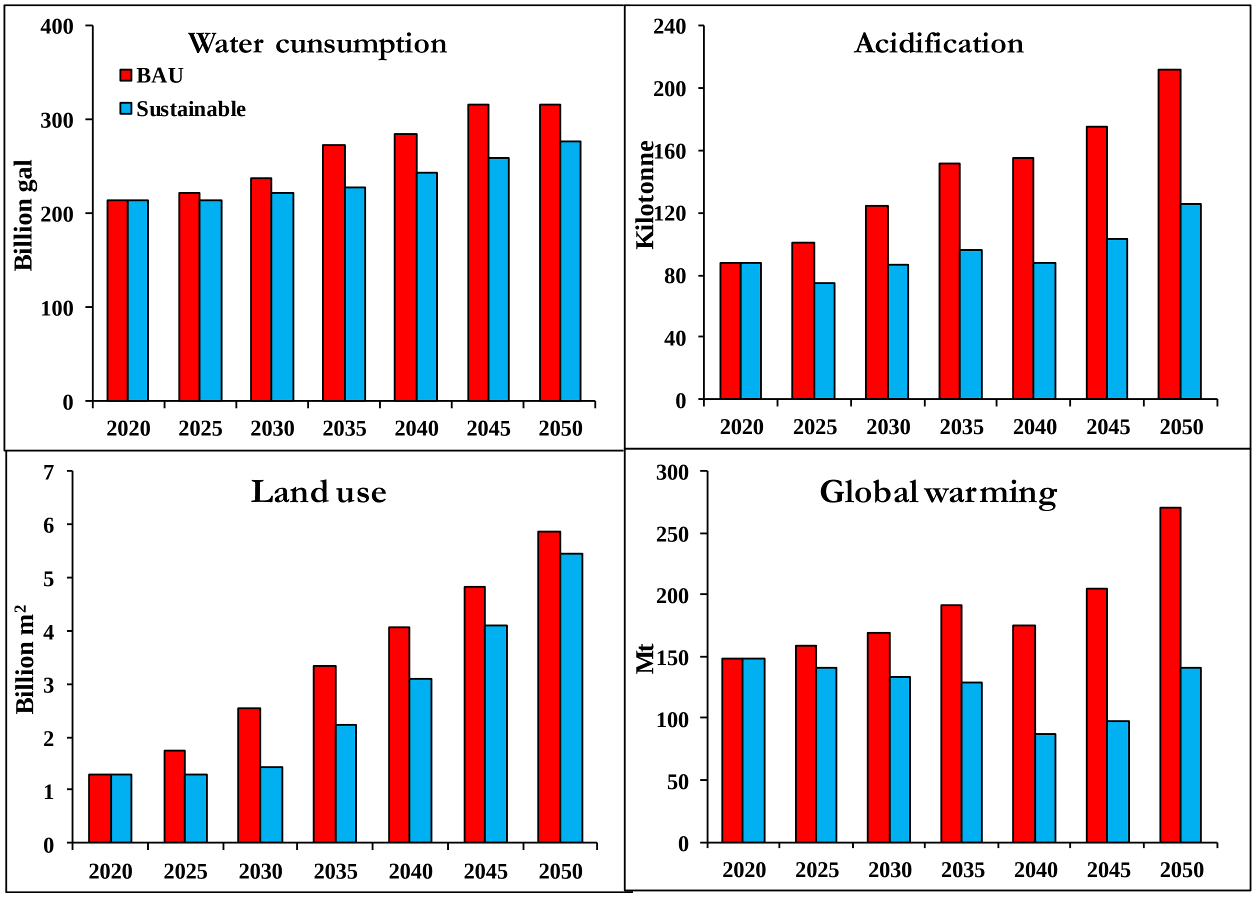

Fig. 10. Total annual environmental impacts of electricity supply in BAU and sustainable schemes

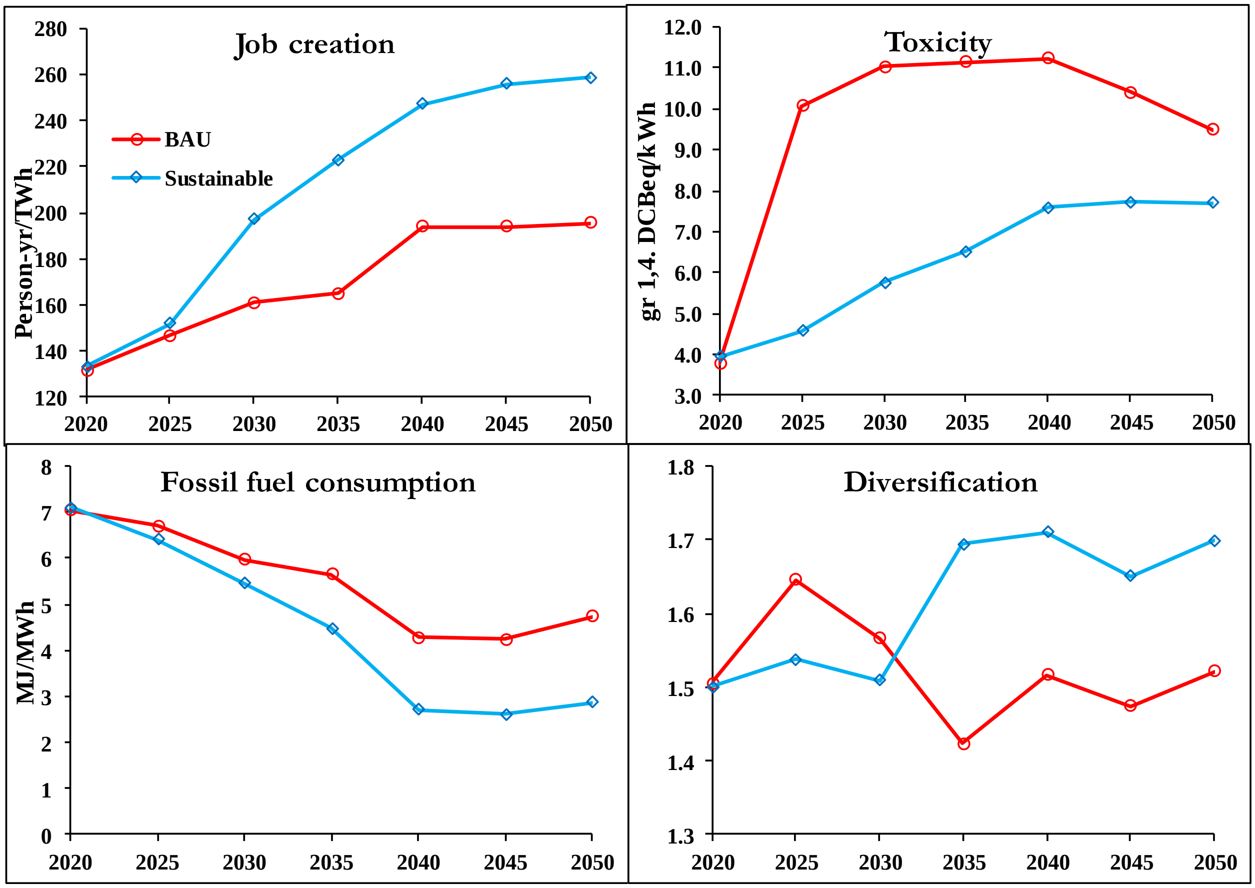

Fig. 11. The trends of social indicators in BAU and sustainable schemes expressed per unit of generation

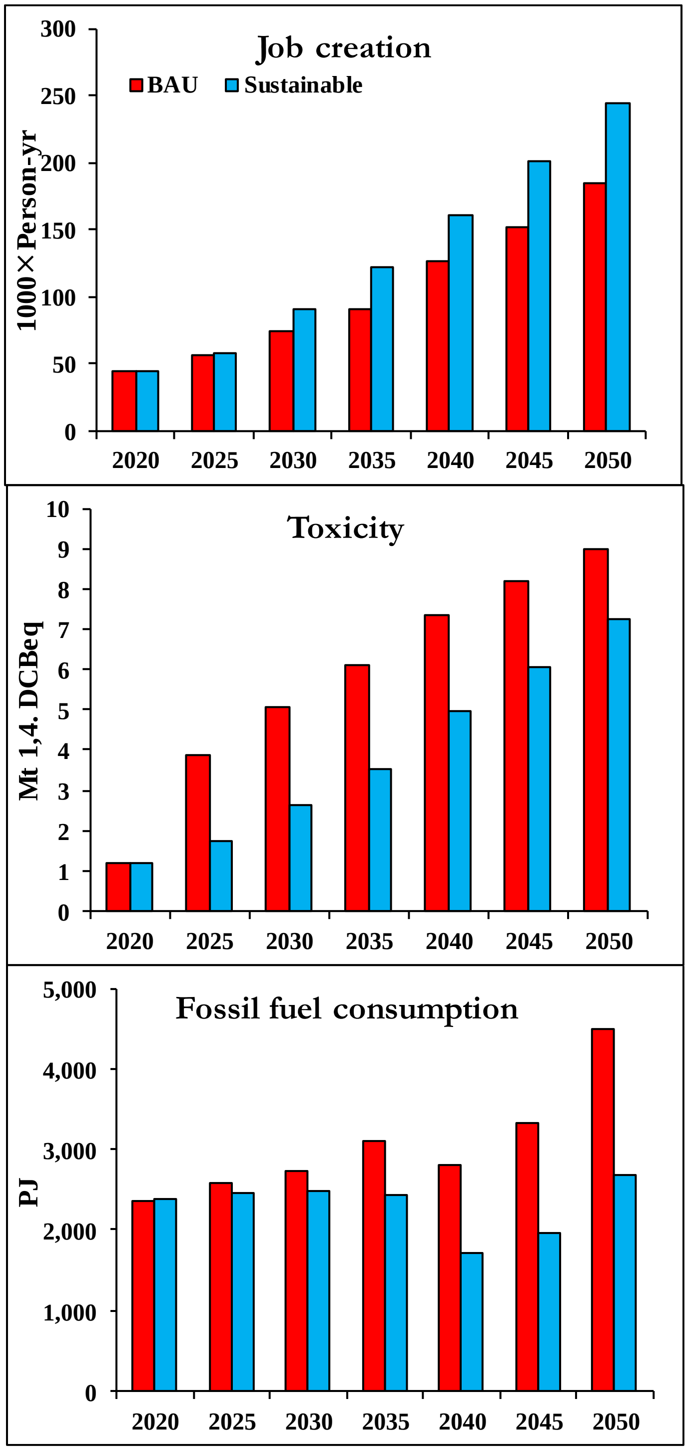

Fig. 12. Total annual social impacts of electricity supply in BAU and sustainable scheme.

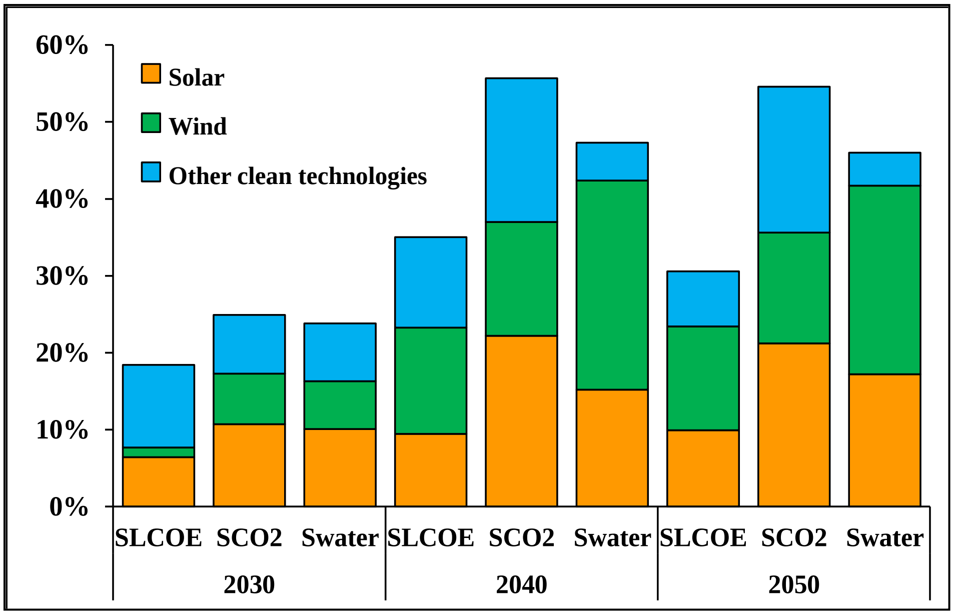

Fig. 13. Generation share of clean technologies in extreme scenarios.

Tables:

Table. 1. The description of the sustainability indicators [55].

Indicator	**Description**	**Unit**
Levelized cost of electricity (LCOE)	Generation cost per unit of electricity	cent/kWh
Economic dispatchability	Ratio of investment cost to LCOE	Percentage
Investment cost	-	cent/kWh
Fuel cost	-	cent/kWh
O&M costs	-	cent/kWh
Fuel price sensitivity	Ratio of fuel cost to LCOE	Percentage
Capacity factor	Ratio of actual electricity output to the maximum possible	Percentage
Construction time	-	Year
Global warming	Greenhouse gas emissions	gr CO_2eq/kWh
Acidification	Emissions of SO_2, NO_x, HCl, and NH_3	gr SO_2eq/kWh
Land use	-	m^2/MWh
Water consumption	-	gal/MWh
Job creation	-	Person.year/TWh
Fossil fuel consumption	-	MJ/MWh
Human toxicity potential	-	gr 1,4 dichlorobenzene (DCB)eq/kWh
Diversification	Power supply diversification	Real number

Table 2. The groups of technologies and their range of share in 2050 generation [56] [57] [11] [58] [59].

Group of technologies	**The range of generation share in 2050 (%)**
Steam power plant	0-10
Combined cycle power plant	20-70
Coal-fired power station	0-15
Gas turbine and gas engine	0-15
Nuclear power	0-20
Hydropower	0-15
Solar power	0-40
Wind turbine	0-25
Other technologies	0-5

Table B1. Techno-economic, environmental, and social parameters of power generation technologies [59] [11] [57] [76] [61] [77] [78] [79] [80] [81] [51] [82] [55] [83].

Parameter[a] / Technology	Capital cost[b]	Fixed O&M cost	Variable O&M cost	Construction time	Lifetime	Efficiency	Self-consumption	Load factor	Maximum annual realizable capacity[d]	Human toxicity potential	Job creation	Acidification potential	Water use	Land occupation
	$/kW	$/kW	$/MWh	year	year	%	%	%	MW	gr 1,4. DCBeq /kWh	Job yr/GWh	gr SO_2-eq /kWh	gal/MWh	m^2 yr/MWh
Solar PV (on-grid, off-grid)	1100-790-630[c], 1500-1000	24, 37	-	1	20	-	-	18, 17	350-6000	21.67	0.87	0.075	26	9.92
Solar thermal	4300-2700	64	-	2	30	-	-	39	350-6000	4.27	0.23	0.032	52	9.00
Onshore wind	1400-1200	48	-	2	20	-	1.4	32	450-6000	6.33	0.17	0.021	0	0.26
Biomass (landfill)	3300	2	1.7	2	20	30	3	70	10-100	38.20	0.21	0.319	35	466.60
Geothermal	5600	84	1.1	7	30	-	8	80	55	8.80	0.25	2.733	135	0.17
Hydropower (small, large)	2000, 1200	14, 10.8	-	4, 7	40, 50	-	0.5	35, 18	20-100, 400	3.58	0.27	0.016	4491	4.44
Nuclear (LWR, ALWR)	4000, 4200-3550	74, 69	0.7, 0.5	7,8	40, 60	31, 33	10, 8	80, 85	-	13.12	0.14	0.037	672	0.54
Combined cycle (conventional, advanced)	700, 1140-840	4.4, 21	0.42, 2.6	5	30	47, 58	1.9	70, 80	-	3.40	0.11	0.221	198	0.41
Gas turbine (conventional, advanced)	550, 780	4.5, 24	0.6, 4.3	2, 3	12, 15	34, 40	0.8	60	-	3.40	0.11	0.221	0	0.41
Gas engine	770	8	5.1	1	10	40	0.7	90	100-700	3.40	0.11	0.221	0	0.41
Coal power plant (conventional, advanced, IGCC)	1600, 2200, 5500	64, 88, 92	0, 0, 6.5	3, 4, 4	30, 40, 40	35, 46, 45	5.5, 6.5, 10	75, 80, 80	-	57.34	0.11	0.836	505	27.28
Steam power plant	900	9.5	0.48	5	30	38	6.8	70	-	3.40	0.11	0.221	826	0.41

[a] The values separated by comma are associated with different types of a technology for example conventional or advanced.
[b] The first and second values refer to the present and 2030 capital cost, respectively.
[c] The first, second, and third values refer to the present, 2030, and 2050, respectively.
[d] The first and second values refer to the present and 2050, respectively.