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A multicriteria modeling approach for evaluating power generation scenarios under uncertainty: The case of green hydrogen in Greece

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ABSTRACT

Clean energy technological innovations are widely acknowledged as a prerequisite to achieving ambitious long-term energy and climate targets. However, the optimal speed of their adoption has been parsimoniously studied in the literature. This study seeks to identify the optimal intensity of moving to a green hydrogen electricity sector in Greece, using the OSeMOSYS energy modeling framework. Green hydrogen policies are evaluated, first, on the basis of their robustness against uncertainty and, afterwards, against conflicting performance criteria and for different decision-making profiles towards risk, by applying the VIKOR and TOPSIS multi-criteria decision aid methods. Although our analysis focuses exclusively on the power sector and compares different rates of hydrogen penetration compared to a business-as-usual case without considering other game-changing innovations (such as other types of storage or carbon capture and storage), we find that a national transition to a green hydrogen economy can support Greece in potentially cutting at least 16 $MtCO_2$ while stimulating investments of EUR 10–13 bn. over 2030–2050.

1. Introduction

Apart from significant progress in energy efficiency and electrification of the energy system, mitigating climate change will require high levels of innovation in clean energy technologies [1]. Of the available innovative alternatives, green hydrogen is of increasing interest, currently featuring an unprecedented political and business momentum around the world [2,3]. This is partly due to increasing carbon prices and the ever-decreasing costs of renewable technologies [4,5]. Green hydrogen could offer the missing piece of the puzzle in the energy transition, primarily by stabilizing renewable power generation through storage, thereby reducing curtailment in grids [6]. It may also contribute to the decarbonization of hard-to-abate sectors (e.g., transport), where electrification is at best an inefficient option [7,8].

The establishment of a green hydrogen economy is particularly relevant for countries like Greece, which present a great technical potential of variable renewable electricity generation [9]. As such, Greece could achieve its ambitious energy and climate targets [10] by tapping into its green hydrogen potential, exploiting in parallel the side-effects of a green hydrogen economy (e.g., in terms of employment) [11]. In this respect, the Greek government has undertaken significant steps towards paving the way to green hydrogen-powered electricity. Indicatively, a national committee was recently established to design the national strategy for hydrogen, while five proposals about hydrogen projects were submitted to the European Commission (EC), with the aim of including them in the European Significant Projects of Common European Interest [12,13].

Formulating the appropriate policies that will successfully lead to

Abbreviations: EC, European Commission; OSeMOSYS, Open Source energy Modeling SYStem; TOPSIS, Technique for Order of Preference by Similarity to Ideal Solution; MCDM, Multiple-Criteria Decision-Making; ESOM, Energy System Optimization Model; COPRAS, Complex Proportional Assessment; SAW, Simple Additive Weighting Choosing By Advantages; MACBETH, Measuring Attractiveness by a Categorical Based Evaluation Technique; PROMETHEE, Preference Ranking Organization METHod for Enrichment Evaluation; AHP, Analytic Hierarchy Process; BAU, business-as-usual; PV, solar photovoltaics; CSP, Concentrated Solar Power; RES, Reference Energy System; R2DSS, Regret-Regret Decision Support System.

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net-zero emissions is a challenging task that entails decisions on the appropriate speed of action, such as the rate of penetration of clean fuels into the energy mix, towards achieving a wide range of objectives (e.g., social, macroeconomic) alongside energy and climate targets [14]. However, to date, limited attention has been paid to this aspect in the literature; the time perspective has been generally associated with the timing of attaining specific targets (e.g., net zero emissions) or applying a targeted policy (e.g., technology phase-out), rather than with the intensity of action—especially when it comes to adopting new clean technologies.

Furthermore, inherent aspects of energy planning comprise the broad set of considerable trade-offs that a policy measure or strategy features among conflicting objectives [15], as well as the involvement of various stakeholders in the process, who may have divergent preferences and conflicting points of view (multi-actor problem) [16]. In this respect, cost-optimization exercises—in which a model internally calculates the cost-optimal trajectory of the power sector—are not well equipped to produce robust energy planning insights alone. This is because a policy scenario that does not comply with the cost-optimal pathway may better serve decision makers when additional targets to the system cost are considered [17]. Moreover, energy planning at its nature is subject to various uncertainties [18], since the time horizon of energy policies spans over many years ahead, while the complex energy-economic interactions render the energy system trajectory's postulation a challenging task [19].

In this context, this study contributes to the literature by introducing an energy planning decision-support framework featuring a novel integration of an energy-system optimization model with different multi-criteria analysis methods and regret measures, allowing to identify the optimal speed of diffusion of anticipated, game-changing technologies in the power sector, considering the behavior of decision makers towards uncertainty. The latter is achieved through combining regret measures and multicriteria methods of a different rationale, thereby producing tailor-made results for different decision-maker risk profiles. The other novelty of this study lies in developing and using a model of the power sector of Greece with high technological detail and time resolution, while providing the framework as openly and transparently as possible.

The study further applies the proposed regret analysis-based modeling approach to understand how fast new clean technologies may emerge in the Greek power sector, focusing on the penetration of green hydrogen over the 2030–2050 period. In this endeavor, based on the capacity of the Greek power sector for clean electricity generation [20], various hydrogen strategies are formulated, each of them entailing a different rate of hydrogen penetration in the energy mix for electricity storage purposes. Also, an unconstrained case featuring no explicit provision about green hydrogen is considered, serving as the baseline scenario of the analysis. The inherent uncertainty of energy planning is addressed by assuming different trajectories of electrolyzer efficiency and carbon pricing, considering that they may vary simultaneously. As a result, 45 power generation scenarios are formulated and computed with an implementation of the Open Source energy Modeling SYStem (OSeMOSYS) framework for the Greek power sector over 2015–2050, thereby identifying the cost-optimal system configuration subject to the target green hydrogen production. To identify the optimal policy in the presence of uncertainty, we apply the R_2DSS method presented in Ref. [21]. At the first stage, two variants of the VIsekriterijumska optimizcija i KOmpromisno Resenje (in Serbian), or VIKOR, multi-criteria decision analysis method [22] are employed to evaluate the robustness of the selected policies against uncertainty. At a second stage, both VIKOR and the Technique for Order of Preference by Similarity to Ideal Solution, or TOPSIS [23], are applied to support the evaluation of their total performance with respect to economic, environmental, and technical criteria, with the aim to identify the one that best serves the preferences of policymakers in the light of uncertainty. These two frameworks constitute two widely established distance-based Multiple-Criteria Decision-Making (MCDM) methods, meaning that they take into account the geometric distances of each alternative from an idealized (theoretical) solution.

The rest of the paper is organized in five sections. Section 2 presents the main implementations of MCDM in the field of energy planning in the literature, with a focus on hydrogen applications and Greece, as well as on relevant uncertainty analysis. Section 3 introduces the power generation scenarios formulated in this study and discusses the OSeMOSYS model implementation for Greece, as well as the tools and methods used to simulate and evaluate the scenarios from an MCDM perspective while accounting for uncertainty. Section 4 presents and discusses the results of the analysis, while Section 5 offers conclusions, policy implications, and insights into prospects for further research.

2. Literature overview

A significant body of the energy planning literature has applied MCDM approaches. Such studies are typically conducted in a quantitative setting, by exploiting data associated with the evaluated energy policies (e.g., targets, assumptions, etc.) or the output of an energy system optimization model (ESOM); in a qualitative setting, based on the evaluation performed by stakeholders or experts; or in a hybrid setting, combining the two approaches. Table 1 presents a non-exhaustive overview of MCDM studies on energy planning for Greece [24–28], on a regional or national level, and of studies on hydrogen technologies [16,29,30].

Among these relevant studies, we observe that the complex interactions of/within the energy system are rarely quantitatively modeled (e.g., using ESOMs), but are rather assumed as reflected in the official datasets of the studied policies, to which these studies typically anchor. Another gap lies in the qualitative nature of many studies, based at least in part on the personal perspectives/preferences/viewpoints driving the analysis, thereby leading to possible bias in results and policy implications. Nevertheless, and despite the diversity of MCDM methods employed in this body of literature reflected to some extent in Table 1, there can be observed a pattern in the selection of the evaluation criteria (Table 2).

Finally, a key characteristic of energy planning is its inherent uncertainty. Energy policies usually span many years in the future, which implies a wide range of scenarios about the potential evolution of the main aspects of an energy system (e.g., costs, prices, demand, etc.). This type of uncertainty is broadly defined as 'parametric uncertainty' and represents the challenges in defining the input assumptions of ESOMs [37]. Various approaches have been adopted to handle this type of uncertainty, mainly appertaining to some form of scenario analysis for drivers, such as energy prices [38] or energy demand [39]. The examined scenarios are typically accompanied by sensitivity analysis with respect to the uncertain parameters (e.g., electric vehicles' battery costs [40]), considering one varying factor per case. Stochastic approaches have also been used [41], considering probability distributions for key input parameters [42]; although capturing a relatively wider spectrum of uncertainty, however, they present challenges in implementation and may feature arbitrarily selected probability distributions, thereby leading to bias [43]. MCDM studies have also attempted to deal with uncertainty derived from imprecision on parameter values of decision aid models, with minimax regret analysis being among the prevalent approaches to handling uncertainty [44], widely deemed to enable decision makers to produce rational decisions under uncertain input data [45]. Notably, the original VIKOR method has been extended to cope with various forms of uncertainty, by considering interval numbers for the payoff table [46], incomplete criteria weights [22], or stochastic data [47,48]. Nonetheless, among both the selected studies and the broader scenario modeling literature, uncertainty has not, or only partly, been considered [19], primarily focusing on single-factor sensitivity analysis (e.g. Ref. [49]) and thus not doing justice to the real-world complexity of the energy system.

Table 1
Literature overview of Multi-criteria Decision Making (MCDM) studies in energy planning with a focus on Greece and/or hydrogen.

Study	Objective	MCDM Method	Uncertainty Treatment	Region
D'Amore-Domenech et al. [29]	Selection of the optimal electrolysis technology for green hydrogen	AHP, COPRAS, SAW, TOPSIS, CBA	No	–
Diakoulaki & Karangelis [24]	Selection of the optimal power generation scenario	PROMETHEE	No	Greece
Feitosa & Costa [16]	Selection of the optimal energy technology for hydrogen production	MACBETH	No	Brazil
Georgopoulou et al. [25]	Selection of the optimal power generation scenario	ELECTRE III	No	Crete, Greece
Marinakis et al. [31]	Selection of the optimal power generation scenario	Multi-criteria Ordinal Regression	No	Evrotas, Greece
Mourmouris & Potolias [28]	Selection of the optimal production per renewable technology	REGIME	No	Thasos, Greece
Pilavachi et al. [30]	Selection of the optimal energy technology for hydrogen production	AHP	No	–
Tsoutsos et al. [26]	Selection of the optimal power generation scenario	PROMETHEE I and II	No	Crete, Greece
Trachanas et al. [21]	Selection of replacement technology for lignite power plants	VIKOR with incomplete weights	Yes	Ptolemaida, Greece

COPRAS: Complex Proportional Assessment, SAW: Simple Additive Weighting, CBA: Choosing By Advantages, MACBETH: Measuring Attractiveness by a Categorical Based Evaluation Technique, ELECTRE: ELimination Et Choix Traduisant la REalit (in French), PROMETHEE: Preference Ranking Organization METHod for Enrichment Evaluation, AHP: Analytic Hierarchy Process.

3. Methodology

3.1. Policies for green hydrogen

To shed some light on the speed, at which clean fuels should be introduced into Greece's energy mix, five strategies are formulated regarding the penetration of green hydrogen in the country's power sector. The first one encompasses the targets and policy measures already undertaken by the Greek government, as mainly described in the country's National Energy and Climate Plan (NECP), without any additional measures after 2030. These targets are mainly related to the share of renewables in power generation (65% in 2030) and the revised target of lignite phaseout by 2025. Therefore, this policy scenario could be regarded as a reference or 'business-as-usual' (BAU) scenario, in which no explicit provision is made for the share of green hydrogen in the energy mix.

Table 2
Evaluation criteria typically used in MCDM studies in the spectrum of energy planning [24–30,32–36].

Family Criterion	Indicators
Economic	Investment costs[×], Operation and Maintenance (O & M) Cost[×], Impact on National Industry[∗], Cost of production[×], Fuels cost[×], Levelized cost of saved energy[×], Realization Time[□], Nominal lifetime[□], Payback Period[□]
Technical	Guaranteed energy[∓], Efficiency[⊤], Diversity of installed power[⊤], Energy dependency rate[⊤], Availability[∗], Reliability[∗], Exergy[⊤], Operationality[∗], Stability of the network[∗], Maturity of technology[∗], Fuels savings [¥], Safety of supply[∗], Available power during peak load[∓], Power generation capacity[∓]
Environmental	Greenhouse gas emissions (e.g., CO_2, NOx) [§], Land use[◊], Visual impact-amenity[∗], Environmental impact[∗], Air quality[◊], Noise[∗],[∫], Natural sources depletion[¥], Risk of climate change[⊤], Risk of environmental impact[∗], Mortality rate due to technology[⊗]
Social-Political	Creation of working positions[∗],[~], Public health[∗], Local income[∗], Contribution to regional development and welfare[∗], Social cost[ˆ], Social Acceptability[∗], Social benefits[∗], Risk of harm or injury[∗], Cohesion to local activities[∗]

[×] monetary units (per unit of energy).
[∗] ordinal scale.
[□] time unit.
[∓] units of capacity.
[⊗] number of deaths per unit of energy.
[¥] units of energy (per unit of time).
[⊤] unit-free measure.
[ˆ] monetary units per number of people.
[~] number of people.
[§] unit of mass (per unit of time).
[∫] unit of noise by number of people.
[◊] unit of land (per unit of energy).

On top of that baseline, four additional policy scenarios are considered *("HYD-SPEED1", "HYD-SPEED2", "HYD-SPEED3"*, and *"HYD-SPEED4")*, with each envisaging different speed of green hydrogen

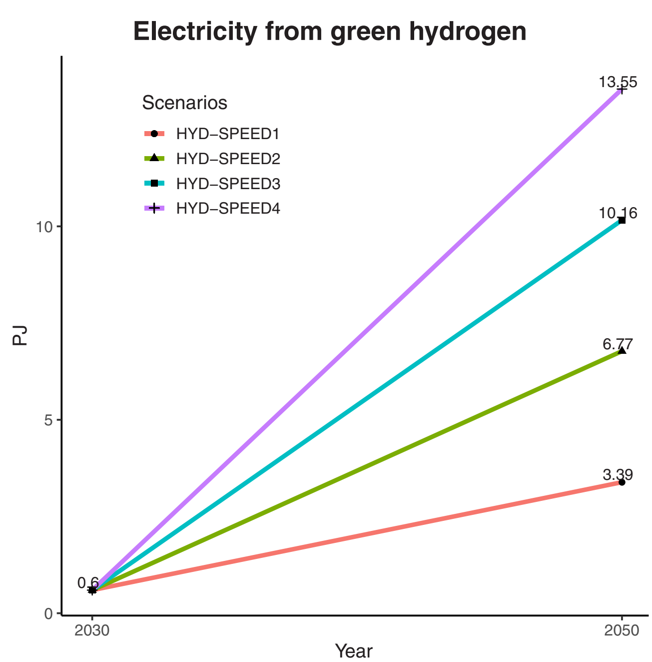

Fig. 1. Final electricity demand produced from hydrogen assumed across the policy scenarios of the study over the 2030–2050 period.

diffusion in the Greek power sector after 2030, as shown in Fig. 1, for electricity storage purposes. All scenarios foresee the same ratio of green hydrogen in power generation in 2030 (Fig. 1), considering the limitations to the technology's adoption in this decade. However, between 2030 and 2050, the speed of its penetration in the energy mix varies among the scenarios: from a green hydrogen share of 5% (12.19 PJ) of final electricity demand in 2050 in *"HYD-SPEED1"* to 20% (40.18 PJ) in *"HYD-SPEED4"*.[1]

It should be noted that, in the context of this study, green hydrogen is assumed to be produced exclusively from electrolysis using RES, and to be used only for electricity storage purposes. Direct final use of green hydrogen—e.g., in the transport sector—is not considered [50].

3.2. OSeMOSYS-Greece

These policy scenarios are modeled in an implementation of the OSeMOSYS framework [51], which offers a dynamic, deterministic, technology-rich, bottom-up, linear-programming ESOM for medium-to-long-term energy planning. OSeMOSYS is used to identify the most cost-efficient way (i.e., minimization of discounted system's cost), in terms of capacity and electricity produced per technology, to meet the exogenously defined final energy demand with respect to existing technological characteristics (technology costs, lifetime, etc.) and system constraints (e.g., GHG emission limits and renewable targets). The model adopts a perfect foresight rationale and assumes perfect competition market conditions to calculate the optimal power mix and the entailed capital and operation costs on an annual basis, with respect to the long-term evolution of the cost dynamics in the power sector.

OSeMOSYS was preferred due to its flexibility to adjust to the particularities of the modeling exercise (i.e., it is structured in code blocks), its open-source nature, the large underlying community, and the wide range of existing applications: it has been used in numerous studies at global [52], continental [53], national [54], and regional levels [55]. The scope of these applications ranges from the long-term impact of carbon pricing on the power sector [55], to land requirements of renewable power expansion [56] and to repercussions of national energy policies [57] via soft-linkages with macroeconomic models.

In this study, an implementation of OSeMOSYS is designed and calibrated to represent the idiosyncrasy of the Greek electricity system over the 2015–2050 period (*OSeMOSYS-Greece* onwards). The rationale behind selecting 2015 as the base year of the analysis refers to calibrating the model with historical data rather than projections at the first modeling horizon's years, thus ensuring a smooth starting point of the calibration procedure. To adjust OSeMOSYS to efficiently represent the Greek power sector, a number of technoeconomic parameters are inserted into the model, as well the current and prospective structure of the Greek power sector. This structure is shown in Fig. 2, which illustrates the reference energy system of the Greek power sector. In this figure, the entire range and flow of processes (from collecting primary energy sources to delivering electricity to final demand sectors) are depicted in an abstract way. Nodes represent power technologies, while arrows depict flows of energy carriers coming in or exiting from technologies. The mixture of power technologies considered comprises both the existing technologies in the Greek power sector (squares) and those expected to grow in the coming years ([20,58]) and, thus, introduced in the modeled pathways. The latter include geothermal, offshore wind, CSP, electrolyzers, fuel cells, and hydrogen storage ("distorted" squares). As illustrated in Fig. 2, renewable technologies can channel their output either directly to the grid or as input to hydrogen production (when not absorbed by the grid), which in turn is transformed into electricity via fuel cells, before flowing toward final electricity demand. Therefore, hydrogen is assumed to be produced only for electricity storage purposes, meaning that no direct consumption of hydrogen is assumed in this study. The electricity trade links of Greece with Albania, Bulgaria, North Macedonia, Turkey, and Italy are also considered and modeled (Fig. 2).

Regarding technoeconomic parameters and core projections about the evolution of the country's power sector (e.g., final electricity demand, carbon pricing, etc.), the datasets reported in the Greek government's long-term strategy [20] are selected. In cases of data unavailability, we use values from other studies with a global scope (e.g., Refs. [50,59,60]) and/or employ online simulators to estimate how the climatic conditions of various regions of the Greek territory affect the variable power generation [61]. Fig. 3 presents the adopted capacity factors for the wind- and solar-based technologies of the system across the time slices of the modeling framework. Moreover, the demand profile of the Greek power sector is extracted from the ENTSO-E database [62] and defined over 24 time slices (twelve seasons, two daily time brackets), while capital cost is set in the order of 8% [20].

All cost figures are inserted in the model in constant USD_{2015}, taking into account a currency conversion rate of 1.128 USD/Euro (2015 average) and the inflation of Greek economy [63]. Regarding energy flows with other countries, they are defined exogenously, using the projected electricity imports from the EU reference scenario [50] and assuming that exports remain constant as a ratio of final demand throughout the modeling period, to avoid abrupt changes to power generation due to amendments to price dynamics. To tailor the model to the particularities of the Greek power sector over existing power capacities per technology and their potential yearly changes, we examined relevant national studies [64] and historical data (e.g., Ref. [65]). Table 3 presents the key input data utilized in OSeMOSYS-Greece to illustrate the current and potential state of the power sector of Greece, for three indicative years: 2015 (base year); 2030 (medium term); 2050 (long term). All simulations of the OSeMOSYS implementation about the hydrogen policy scenarios in the Greek power sector are solved with the GLPK linear-programming solver [66], while the graphical representation of the results is made with the ggplot2 package for R [67].

3.3. Uncertainty treatment

As discussed in Section 2, the results of an ESOM are highly dependent on the selected parameters that represent the characteristics of the energy system. In this respect, our study aims to identify the most robust policy, against the variability that input parameters could feature. Considering that the probability distributions describing the variability of input parameters are not available, uncertainty is handled by assuming discrete divergent uncertainty scenarios about the efficiency of electrolyzers and carbon prices, which are both important and highly uncertain. We do not consider uncertainties over the costs of critical technologies, as green hydrogen production is defined exogenously—meaning that, apart from impacting system costs, considering uncertainty scenarios of varying costs for green hydrogen technologies would not affect the investment decisions made in the model. In contrast, considering different assumptions over the efficiency of electrolyzers, ceteris paribus, can lead to different amounts of clean electricity required to achieve the desired green hydrogen production levels, and therefore to different optimal system configurations. It is noteworthy that the proposed approach can be adapted for any (number of) variable parameters. Moreover, each uncertainty scenario foresees the variability of these parameters simultaneously (i.e., it handles more than one varying factor).

Three uncertainty scenarios are assumed about the efficiency of electrolyzers: the *"average-electrolyzer efficiency"* uncertainty scenario *(Ev)*, entailing an efficiency level derived from the literature [20,60]; the *"increased-electrolyzer efficiency"* scenario, foreseeing efficiency up by 20% compared to the average case (*Ev*+20%); and the

[1] It should be noted that 1.46 units of hydrogen are required to produce one unit of electricity via fuel cells and 1.22 units of electricity to produce one unit of hydrogen (1.27 in 2030; 1.18 in 2050), on average over the 2030–2050 period [50].

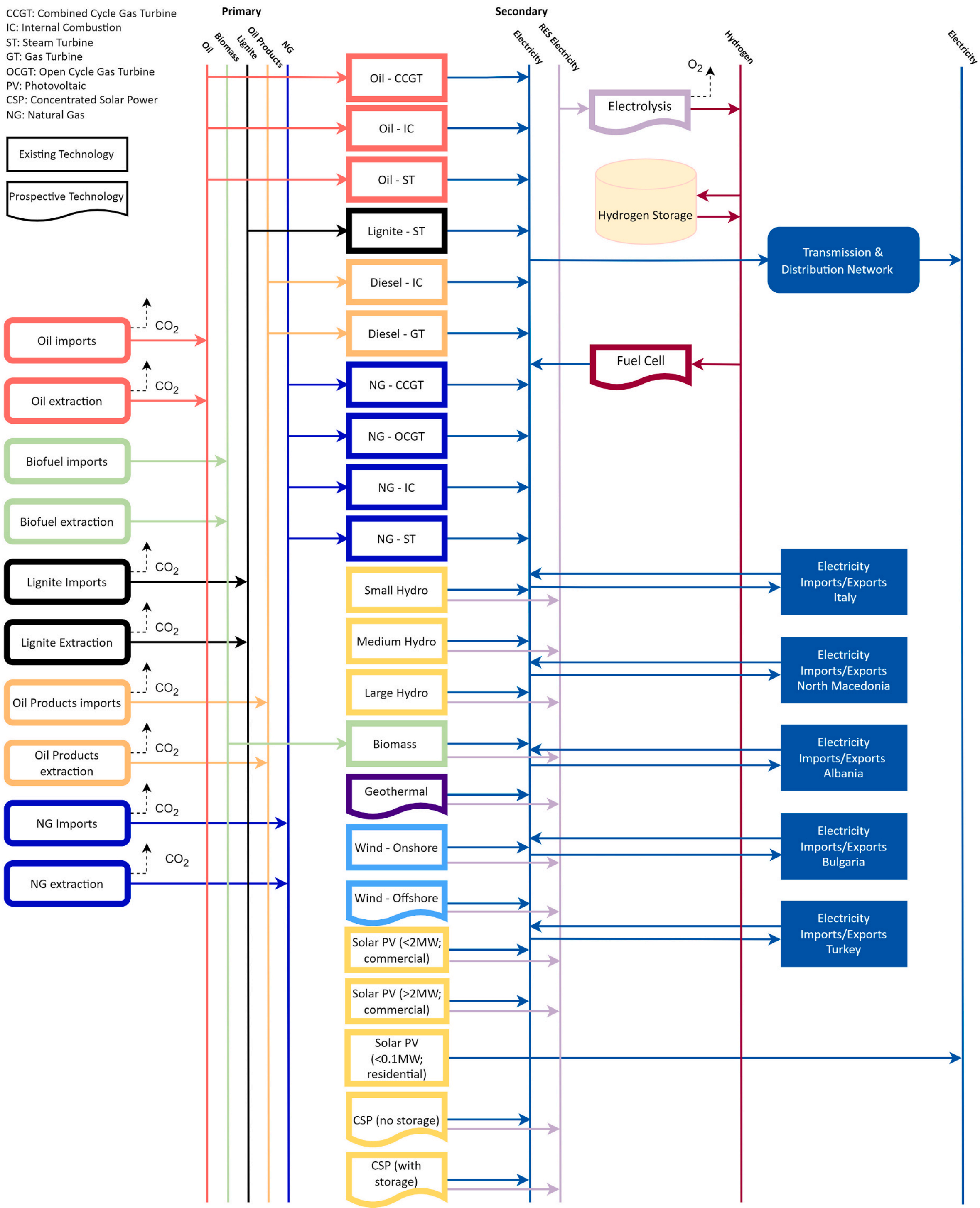

Fig. 2. Reference Energy System of the Greek power sector considered in this study.

"*decreased-electrolyzer efficiency" scenario,* anticipating efficiency down by 20% relative to the average case (*Ev*-20%). Similarly, for the imposed carbon prices, three uncertainty scenarios are assumed: the "*average carbon-pricing*" uncertainty scenario (*Pv*) based on projections [20]; the "*increased carbon-pricing*" scenario, with increased carbon prices by 30% compared to the average case (*Pv*+30%); and the "*decreased carbon--pricing*" scenario, with lower carbon prices by 30% compared to the average case (*Pv*-30%). The stress test level for each parameter is set according to the variability that their values may present onwards. All possible combinations of these factors are considered, resulting in SC_j ($j=1, \ldots, 9$) uncertainty scenarios (Fig. 4). Each of the five policy scenarios is simulated across all 9 uncertainty scenarios, thus resulting in 45 power generation scenarios.

3.4. Multi-criteria decision analysis

The first step towards evaluating the policy scenarios from a multi-criteria perspective is the selection of the performance criteria against which to assess these scenarios. This is done with the view to incorporating those vital aspects of energy planning, which can be measured quantitatively based on the results of the employed energy model. Therefore, other aspects that cannot be directly drawn from OSeMOSYS-

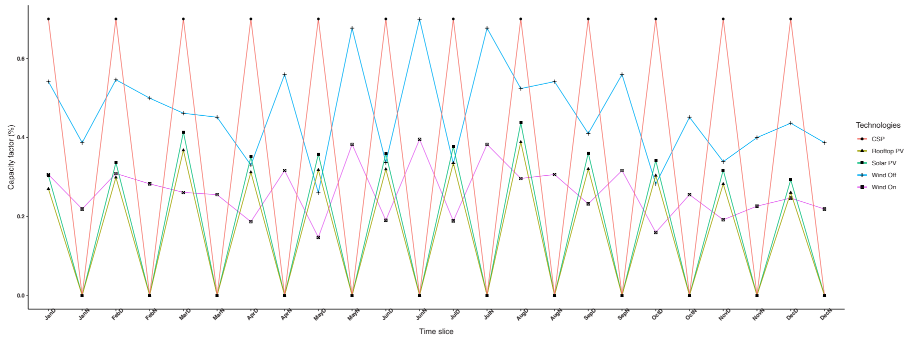

Fig. 3. Adopted capacity factors for the variable renewable power generators of the system, across the time slices of the modeling framework. For the naming of time slices, the first three letters of the entailed month and the letter D or N, for the day- and night-time bracket respectively, are utilized.

Greece are excluded from the analysis. The selected family of criteria, displayed in Table 4, include environmental (CO_2 emissions), economic (capital investments, variable, and fixed operating costs), and technical (import dependency, total system capacity) criteria.

For the purpose of evaluating the different hydrogen penetration policy scenarios against these criteria and in the presence of various scenarios, we use the Regret-Regret Decision Support System (R_2DSS) methodology developed in Ref. [21], which is based on a two-stage VIKOR regret analysis. The main advantage of the distance-based VIKOR methods lies in measuring the trade-off between 'group utility' and 'individual regret' [46]. As per the original VIKOR method [69], an aggregated regret across scenarios (S) and a maximum/worst regret for not achieving the ideal state (R) are used separately to evaluate the robustness of the policy scenarios. This yields a classical MCDM problem that can be solved with any MCDM method allowing to reach a compromise solution.

First, we calculate these two regret values (R and S) for each policy scenario, using the following algorithm of this VIKOR regret analysis. Given a set of alternatives $A = \{A_1, \dots, A_m\}$ that are evaluated across a set of criteria $C = \{C_1, \dots, C_n\}$ with consequences f_{ij}, where I, J denote the sets of benefit- and cost-type criteria respectively and $w_j, j = 1, \dots, n$ stand for criteria weights, the steps of the classical VIKOR algorithm can be expressed as follows:

(V.a) Determine the best f_j^* and the worst f_j^- criteria values through:

$$f_j^* = \begin{cases} \max\limits_i f_{ij}, j \in I \\ \min\limits_i f_{ij}, j \in J \end{cases} \tag{1}$$

$$f_j^- = \begin{cases} \min\limits_i f_{ij}, j \in I \\ \max\limits_i f_{ij}, j \in J \end{cases} \tag{2}$$

(V.b) Calculate values S_i and R_i as follows:

$$S_i = \sum_{j=1}^{n} w_j \left| \frac{f_j^* - f_{ij}}{f_j^* - f_j^-} \right| \tag{3}$$

$$R_i = \max_j w_j \left| \frac{f_j^* - f_{ij}}{f_j^* - f_j^-} \right| \tag{4}$$

(V.c) Calculate the normalized combination of S_i and R_i, denoted by Q_i, using:

$$Q_i = \nu \frac{S_i - S^*}{S^- - S^*} + (1 - \nu) \frac{R_i - R^*}{R^- - R^*} \tag{5}$$

where

$$S^* = \min_i S_i, S^- = \max_i S_i \tag{6}$$

$$R^* = \min_i R_i, R^- = \max_i R_i \tag{7}$$

and the coefficient ν is introduced to trade off between the two different decision-making perspectives included in the VIKOR context: (i) the "group utility" perspective, represented by metric S and (ii) the "individual regret" perspective, represented by metric R. These are the two most relevant indicators for VIKOR—i.e., those used to assess alternatives based on this method. Ranking the alternatives only with metric S means that, for each alternative, its normalized regret values are summed across criteria, as expressed by (3). This implies that the obtained compromise solution performs well in the majority of the criteria. On the other hand, ranking the alternatives only with metric R means that the solution is obtained based on the maximum normalized regret across criteria as expressed by (4), in turn suggesting that the arising compromise solution does not significantly underperform at each and every performance criterion. As ν varies, we obtain an insight into how robust the solution is when shifting from the one strategy to the other, which together correspond to two different decision maker profiles [46].

(V.d) Rank alternatives with respect to Q.

(V.e) Check compromise solutions regarding acceptable advantage and stability conditions.

The consequences of the payoff table are assumed to vary across discrete scenarios. In this regard, the consequences of alternatives across criteria take the following form:

$$f_{ij}^k, i = 1, \dots, m, j = 1, \dots, n, k = 1, \dots, l$$

At the first stage, two robustness indexes for each alternative are calculated separately. In particular, formulas (3) and (4) with weights $w_j = 1, j = 1, \dots, n$, are employed, expressing the aggregated regret and the maximum regret of alternatives across scenarios, respectively. More precisely, for each alternative – criterion pair, the following values are separately calculated:

$$R_{ij} = \max_k \left| \frac{f_k^{+j} - f_{ij}^k}{f_k^{+j} - f_k^{-j}} \right| \tag{8}$$

and

$$S_{ij} = \sum_{k=1}^{l} \left| \frac{f_k^{+j} - f_{ij}^k}{f_k^{+j} - f_k^{-j}} \right| \tag{9}$$

where

$$f_k^{+j} = \left(\left(\max_i f_{ij}^k \middle| j \in I \right) \text{or} \left(\min_i f_{ij}^k \middle| j \in J \right) \right) \tag{10}$$

$$f_k^{-j} = \left(\left(\min_i f_{ij}^k \middle| j \in I \right) \text{or} \left(\max_i f_{ij}^k \middle| j \in J \right) \right) \tag{11}$$

Stand for the best and worst values in each scenario.

The obtained regret values for the policy scenarios of Section 3.1 form a classical MCDM problem, where all criteria are of cost type

Table 3
Key input data utilized in calibrating OSeMOSYS-Greece to the Greek power sector.

	Input per unit of output			Capital Cost (M$/GW)			Variable Cost (M$/PJ)			Fixed Cost (M$/GW)			Operational life	Construction
	2015	2030	2050	2015	2030	2050	2015	2030	2050	2015	2030	2050	Years	
Coal ST	2.24	2.17	2.13	2328.7	2328.7	2328.7	14.4	13.8	13.1	48.5	38.8	33.6	40	4
Geothermal	–	–	–	6342.7	4731.1	3865.7	1.2	1.2	1.2	95.2	103.3	114.2	35	4
Biomass CHP	–	–	–	2951.2	2761.5	2526.6	1.11	1.11	1.11	53	45.8	43.8	40	3
Diesel GT	2.53	2.44	2.33	600.3	600.3	600.3	8.5	8.5	8.5	19.6	19.6	19.6	30	3
Diesel IC	2.38	2.38	2.38	1109.4	1109.4	1109.4	8.5	8.5	8.5	40.0	40.0	40.0	30	3
T&D Network	1.08	1.08	1.08	1000	907	799	5.6	5	4.44	15.2	13.6	12	40	2
Oil CCGT	1.24	1.2	1.17	1158.6	1054.8	1027.4	7.97	7.97	7.97	16.3	16.3	16.3	30	3
Oil IC	2.38	2.38	2.38	1109.4	1109.4	1109.4	8.5	8.5	8.5	40.0	40.0	40.0	30	3
Oil ST	2.24	2.17	2.13	2328.7	2328.7	2328.7	14.45	13.74	13.11	48.5	38.8	33.6	30	3
Small hydro (<10 MW)	–	–	–	2923.7	2923.7	2923.7923.74	0	0	0	73.5	73.5	73.5	60	4
Medium hydro (10–100 MW)	–	–	–	2457.6	244.8	2923.74	0	0	0	66.2	66.2	66.2	60	4
Large hydro (>100 MW)	–	–	–	1991.5	1966	1920.3	0	0	0	58.8	58.8	58.8	60	4
NG CCGT	1.24	1.2	1.17	1158.6	1054.8	1027.4	7.97	7.44	6.77	16.3	16.3	16.3	30	3
NG OCGT	2.63	2.63	2.63	1017.6	1017.6	1017.6	50.49	50.49	50.49	10.2	10.2	10.2	30	3
NG IC	2.38	2.38	2.38	1109.4	1109.4	1109.4	8.55	8.55	8.55	40.0	40.0	40.0	30	3
NG ST	2.24	2.17	2.13	2328.7	2328.7	2328.7	14.45	13.74	13.11	48.5	38.8	33.6	30	3
CSP (without storage)	–	–	–	6928.3	4412.4	7801.1	0	0	0	206.8	156.8	107.8	25	3
CSP (with storage)	–	–	–	10271.5	5273.9	9344.6	0	0	0	247.8	187.8	129.1	25	3
Solar PV (<2 MW)	–	–	–	683.5	640.0	459.1	0	0	0	21.6	12.4	9.1	30	1.5
Solar PV (>2 MW)	–	–	–	899.3	842.1	604.1	0	0	0	28.5	16.3	12.0	30	1.5
Rooftop Solar PV	–	–	–	2045.1	1092.2	716.4	0	0	0	30.6	18.5	12.0	30	1
Wind Onshore	–	–	–	1551.2	1301.0	1035.0	0	0	0	24.5	22.8	21.8	30	1.5
Wind Offshore	–	–	–	4381.0	2805.4	2590.3	0	0	0	52.6	33.7	30.5	30	3
Electrolyzers	1.4	1.27	1.18	1044.4	672.0	201.6	0	0	0	29.79	15.68	10.08	8.5	1.5
Fuel cells	1.47	1.46	1.46	3690.7	3461.3	2988	0.32	0.32	0.32	63.31	51.92	44.82	20	1.5
Hydrogen storage	1.1	1.1	1.1	1483.33	1093.33	1061.28	0.16	0.20	0.226852	0	0	0	17.5	1.5

	Coal			Oil			NG			Biofuel			Oil products				2015	2030	2050
Fuels price (M$/PJ)	2015	2030	2050	2015	2030	2050	2015	2030	2050	2015	2030	2050	2015	2030	2050	Demand (PJ)	182.8	214.8	243.9
	2.21	2.91	3.56	2.21	2.85	3.56	7.27	8.23	9.87	5.24	5.24	5.24	11.14	11.14	11.14	CO_2 price (M$/Mt$CO_2$)	8.3	85	150

	JanD	JanN	FebD	FebN	MarD	MarN	AprD	AprN	MayD	MayN	JunD	JunN	JulD	JulN	AugD	AugN	SepD	SepN	OctD	OctN	NovN	OctN	DecN	DecN
Demand profile	0.04	0.05	0.05	0.04	0.04	0.04	0.05	0.03	0.05	0.02	0.06	0.02	0.07	0.03	0.06	0.03	0.05	0.03	0.04	0.03	0.04	0.04	0.04	0.05
Year split	0.03	0.05	0.04	0.04	0.04	0.05	0.04	0.04	0.05	0.03	0.05	0.03	0.05	0.03	0.05	0.04	0.04	0.04	0.04	0.05	0.03	0.05	0.03	0.05

CCGT: Combine, Cycle Gas Turbine, IC: Internal Combustion, ST: Steam Turbine, GT: Gas Turbine, OCGT: Open Cycle Gas Turbine, PV: Photovoltaic, CSP: Concentrated Solar Power, NG: Natural Gas, Timeslice naming: [3 first letters of month's name] AND [D: day or N: night].

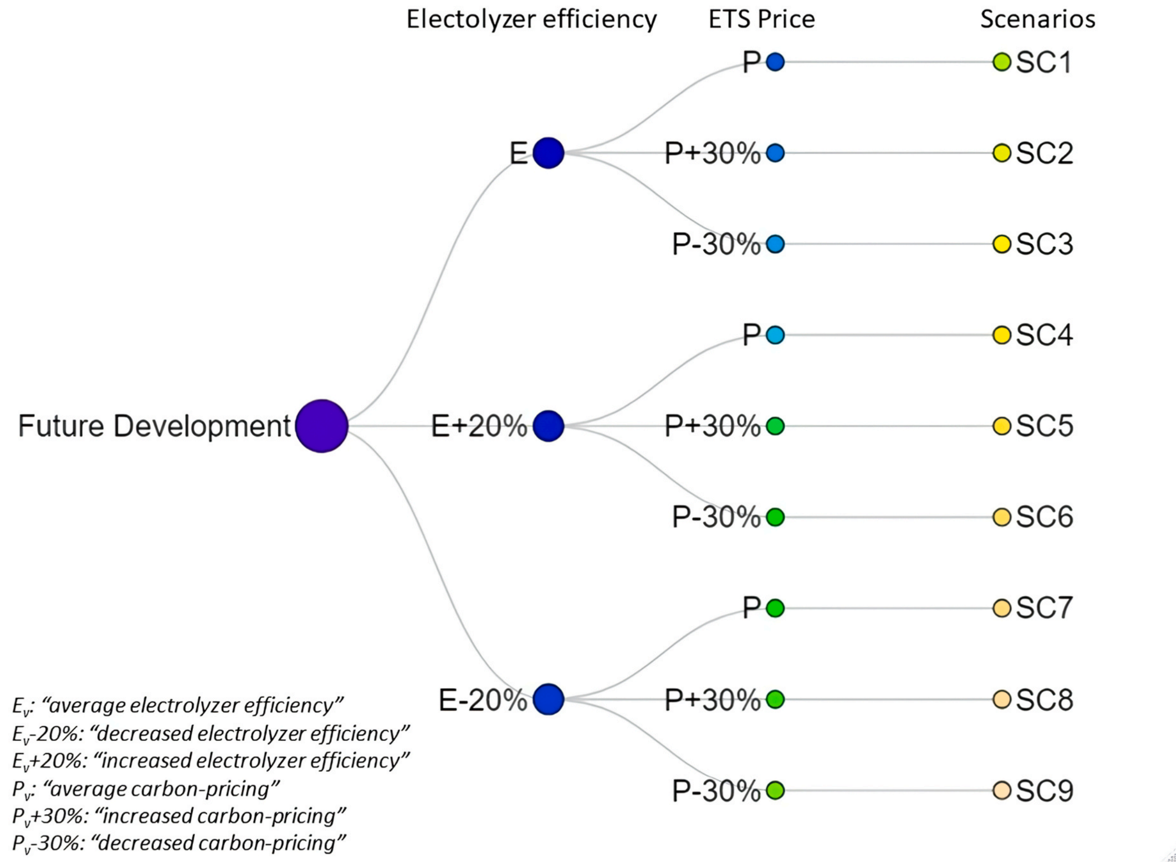

Fig. 4. Levels of electrolyzer efficiency and costs entailed in each uncertainty scenario (SCj, j = 1, …,9) of the study.

Table 4
Structure and attributes of the analysis' evaluation criteria.

Family Criteria	Sub-Criteria	Measuring Unit	Attribute
Environmental	C_1: CO_2 Emissions	Mtn	▼
Economic	C_2: Capital Investments	Million EUR	▼
	C_3: Variable Operating Cost		▼
	C_4: Fixed Operating Cost		▼
Technical	C_5: Import Dependency*	Unit-free measure	▼
	C_6: Total System Capacity	GW	▲

▼*: Cost criterion,* ▲*: Benefit criterion, (*): Imports/Final Demand* [68].

(regret values). In a second step, the classical VIKOR method (steps (V.a) - (V.d) above) is applied to solve the emerging MCDM problem. To obtain robust prioritization for different risk behavior profiles, however, in this step we additionally use the TOPSIS multi-criteria decision-making method [70], allowing to inspect the robustness of results against the MCDM method used. TOPSIS is another distance-based method that has been widely used to support energy and climate policy making [71–73]. Compared to VIKOR, TOPSIS also takes into account the distance from a negative ideal solution, making it more appropriate for conservative decision makers [69]. We use the following TOPSIS algorithm. Given a set of alternatives $A = \{A_1, \ldots, A_m\}$ that are evaluated across a set of criteria $C = \{C_1, \ldots, C_n\}$ with consequences f_{ij}, the TOPSIS method consists of the following steps:

(T.a) Calculate the normalized decision matrix. The normalized values are calculated as:

$$r_{ij} = \frac{f_{ij}}{\sqrt{\sum_{i=1}^{m} f_{ij}^2}} \tag{12}$$

(T.b) Calculate the weighted normalized decision matrix. The weighted normalized values are calculated as:

$$p_{ij} = w_j r_{ij} \tag{13}$$

where $0 \le w_j \le 1$ and $w_1 + \ldots + w_n = 1$.

(T.c) Determine the positive ideal solution (PIS) $P^+ = (p_1^+, \ldots, p_n^+)$ and the negative ideal solution (NIS) $P^- = (p_1^-, \ldots, p_n^-)$ as:

$$p_j^+ = \begin{cases} \max_i p_{ij}, j \in I \\ \min_i p_{ij}, j \in J \end{cases} \tag{14}$$

$$p_j^- = \begin{cases} \max_i p_{ij}, j \in J \\ \min_i p_{ij}, j \in I \end{cases} \tag{15}$$

(T.d) For each alternative, calculate the Euclidean distance from PIS and NIS as:

$$ED_i^+ = \sqrt{\sum_{j=1}^{n} \left(p_{ij} - p_j^+\right)^2} \tag{16}$$

and

$$ED_i^- = \sqrt{\sum_{j=1}^{n} \left(p_{ij} - p_j^-\right)^2} \tag{17}$$

(T.e) Calculate the relative closeness as:

$$D_i = \frac{ED_i^-}{ED_i^+ + ED_i^-} \tag{18}$$

(T.f) Rank the preference order based on the relative closeness—i.e., D_i is the most relevant indicator to use to assess alternatives based on TOPSIS. Given the definition of relative closeness, $D_i \in \lfloor 0, 1 \rfloor$; the higher the value, the better the alternative—a value of $D_i = 0$ indicates an alternative that is equal to the negative ideal solution, while a value of $D_i = 1$ indicates an alternative that is equal to the positive ideal solution.

A similar risk profile classification can be made about the two regret measures of the first stage of the analysis: treating uncertainty based on R would be a better fit for decisions makers that prioritize the aspect of loss, since uncertainty is dealt only by avoiding the worst performance without considering holistic performance (i.e., profit). In contrast, the S metric would better suit decision makers that are willing to undertake some risk.

The entire risk behavior classification, based on the regret analysis metric and the MCDM method, is summarized in Table 5, where decision makers are categorized into "*risk-taking*", "*risk-averse*", and "*risk-neutral*". Risk-takers prioritize performance, even if its full attainment is uncertain and high discrepancies may emerge. In contrast, risk-averse decision makers avoid high inconsistencies between predicted and actual performance, regardless of the sacrifice. Risk-neutral decision makers are in the middle, without preference over undertaking or avoiding risk.

4. Results and discussion

This section discusses the results of the analysis per hydrogen policy scenario across uncertainties and perspectives, over the 2030–2050 period. Detailed results of each simulation are presented in the Appendix. It is noteworthy that, although the modeling horizon spans from 2015 to 2050 on an annual resolution, results are reported over the 2030–2050 period. This is because the core assumptions of the policy scenarios diverge only post-2030—i.e., when hydrogen begins to break into the energy mix at different paces. The performance of each policy scenario is measured based on the cumulative results over the entire reporting period (i.e., 2030–2050).

Based on the results of OSeMOSYS-Greece, a group utility and a maximum regret were calculated per policy, allowing to evaluate how each strategy performs across scenarios and evaluation criteria. These results are illustrated in Fig. 5, showing how VIKOR's S and R values of the first stage of the proposed framework vary (i.e., regret values in terms of S and R across uncertainty scenarios, for each criterion) It is evident that, in both cases, higher regret is associated with higher costs: in the first case (group utility), in terms of higher distance from the optimal state, thus as a higher aggregated opportunity loss; and, in the second case (maximum regret), as the highest deviation from the best state across uncertainty. It should be clarified that hydrogen is excluded from the BAU power generation mix due to high associated costs and not due to prescribed scenario assumptions.

From the group utility perspective, the higher the speed of green hydrogen diffusion, the higher capital investments are required, and the higher the fixed system costs become. As such, the higher the share of green hydrogen in power generation, the poorer the performance of the policies in these dimensions. However, from a variable cost perspective, the contrary is observed. This is mainly due to the larger share of natural gas and the higher reliance on geothermal power for policies of lower rates of hydrogen diffusion, or the higher diffusion of wind and solar coupled with storage for policies of higher hydrogen rates. As far as import dependency is concerned, reliance on energy flows from abroad decreases with higher penetration of green hydrogen, highlighting the parallel drop of natural gas. Similarly, green hydrogen diffusion is beneficial for total installed capacity, primarily due to higher renewable energy capacity and storage. Given that higher penetration of hydrogen leads to lower use of fossil gas, the environmental performance of the system improves (i.e., lower CO_2 emissions) with higher rates of green hydrogen expansion.

Similar overall trends are observed under the maximum regret case, albeit with some discrepancies. These are mainly linked to the equal performance of some policies across uncertainty in import dependency and total system capacity. This stresses that considering the performance of policies across the entire range of scenarios (i.e., group utility case) provides a clearer picture about their desirability per perspective, compared to considering only their worst performance across scenarios (i.e., maximum regret case).

The regrets of the inspected policy scenarios, expressed in VIKOR terms (Q), are depicted in Fig. 6 as a function of the ν coefficient expressing the decision-making strategy. This is a core feature of the VIKOR method and its extensions; via coefficient ν, it allows to trade off the "group utility" strategy (also known as "majority of criteria" strategy), which is expressed through metric S, and the "individual regret" strategy, which is expressed through metric R. In particular, Fig. 6 shows how Q values vary across ν, by adopting either a group utility treatment of the scenarios or a maximum regret one at the first stage. Based on the Q values presented in Fig. 6, the ranks of each policy scenario across ν are derived and depicted in Fig. 7. It is evident from the VIKOR formula (Eq. 5) that, while ν tends to 0, decision makers attribute higher value to Savage's minimax regret ("pessimistic" decision makers); in contrast, as ν approaches 1, they prioritize the current situation considering the expected opportunity loss ("optimistic" decision makers) [22].

As depicted in Figs. 6 and 7, treating uncertainty with the group utility measure results in better merits for policies envisaging higher hydrogen rates while ν tends to 1. In most cases, under the group utility approach, a green hydrogen policy outperforms a policy that does not include green hydrogen in the energy mix (i.e., a policy designed only on the basis of minimizing total cost), irrespective of the green hydrogen growth rate. Similar conclusions are drawn under the maximum regret case. These results imply that green hydrogen-based electricity storage should be an integral part of the transformation of Greece's power sector.

In the maximum regret case, the relation between coefficient ν and hydrogen policy desirability is not as straightforward. In all cases, aiming for a green hydrogen share of 15% is found optimal, with the only exception being for decision makers featuring high frustration against uncertainty ($\nu > 0.75$), who may consider implementing policies of higher green hydrogen rates. However, in case of perceived barriers to achieving as high green hydrogen rates, policymakers may consider implementing lower green hydrogen rates (5%), pinpointing that green hydrogen policies begin paying off only after a certain diffusion level.

For both uncertainty treatment measures, VIKOR results clearly indicate that, on average, an optimal amount of green hydrogen adoption exists for most decision makers. Some deviations emerge for more conservative decision makers. In case that the optimal rate cannot be reached—i.e., system capacity does not suffice to provide for the required renewable energy—completely excluding green hydrogen from power generation remains an option.

Results from the application of TOPSIS, at the second stage of the problem, are depicted in Fig. 8 in terms of closeness to the ideal solution

Table 5
Classification of decision-making attitude towards risk into three classes, with respect to the regret measure and the multi-criteria method used to deal with scenarios and assess performance across criteria, respectively. Regret measures consider the aggregate performance ("Group Utility") or the worst performance ("Maximum Regret") across scenarios, and multicriteria methods examine the distance of alternatives from a positive ideal solution (VIKOR), or from both a positive and negative ideal solution (TOPSIS).

Regret Measure (treatment of scenarios)	Evaluation method	
	VIKOR	TOPSIS
Group Utility	Risk-takers *Decision-makers, who prioritize performance despite high uncertainties*	Risk-neutral *Decision-makers, who display no preference over undertaking or avoiding risk*
Maximum Regret	Risk-neutral *Decision-makers, who display no preference over undertaking or avoiding risk*	Risk-averse *Decision-makers, who tend to place safer bets, even at the expense of high performance*

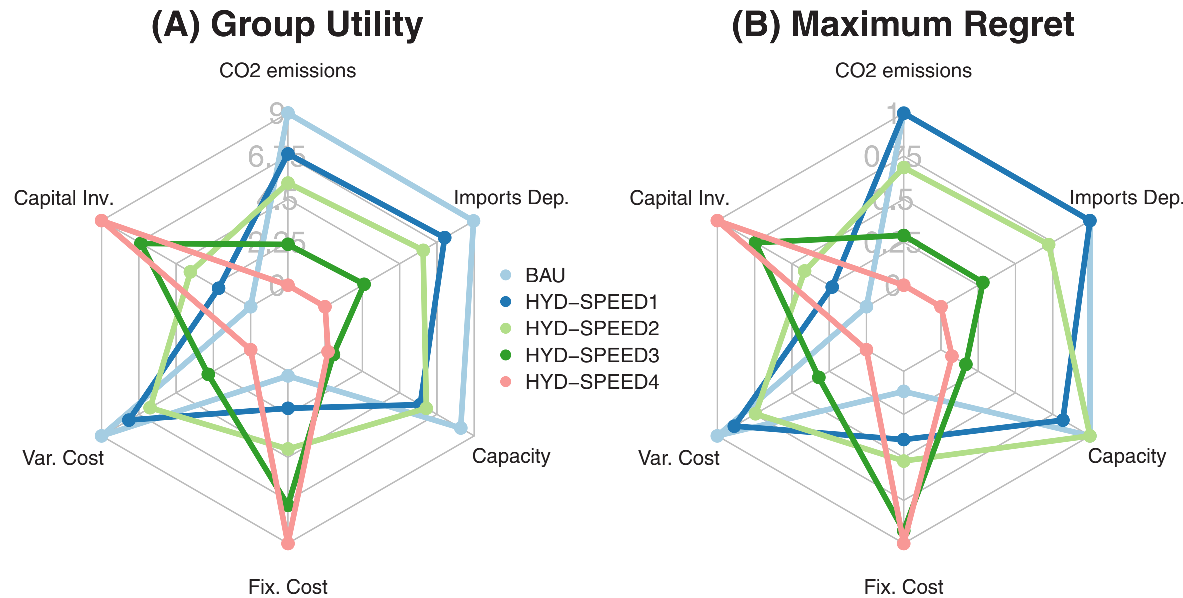

Fig. 5. Regret values of the inspected policy scenarios across uncertainty scenarios based on the VIKOR method: using metric S for the case of group utility regret (A) and metric R for the case of maximum regret (B).

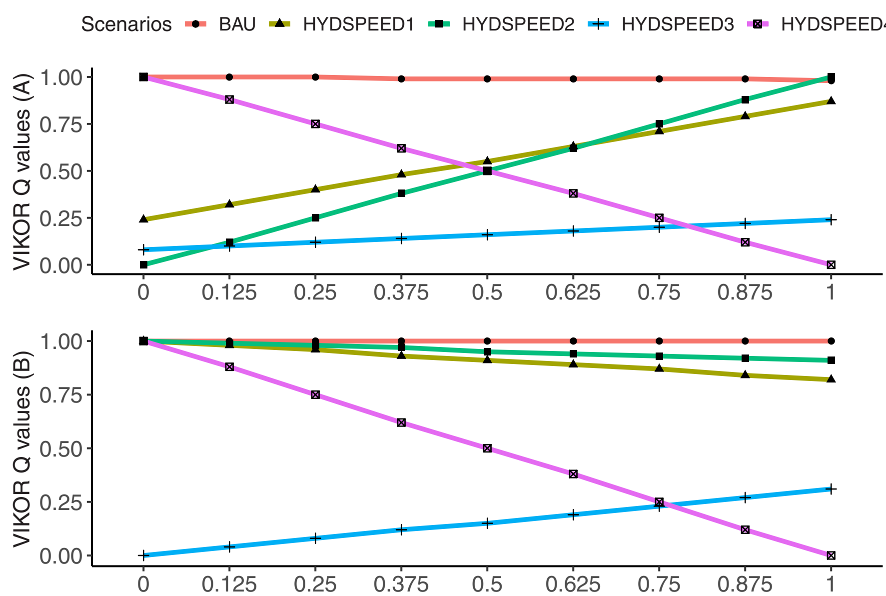

Fig. 6. VIKOR Q values of each policy scenario across ν coefficient values (second stage calculations), when uncertainty is treated with the group utility S metric (A) and the maximum regret R metric (B) (first stage calculations).

(D): a higher D value signifies higher closeness to the optimal solution and thus is preferred by decision makers. Results cover both approaches of treating uncertainty at the first stage of the problem in terms of the regret type used. In the case of group utility, policies entailing green hydrogen-powered electricity in the order of 15% of final demand are found optimal. Higher green hydrogen diffusion rates would yield an insignificantly better performance, hinting at policymakers' indifference from this rate onwards. In case of perceived barriers to achieving this optimal rate, TOPSIS indicates that green hydrogen should not be included in power system configuration. Similarly, in the case of maximum regret, a green hydrogen strategy comprises a favored option only if a green hydrogen-powered electricity share of 15% or more can be achieved by 2050. However, in this case, adopting higher green hydrogen diffusion rates would better serve decision makers. It should be noted that TOPSIS results under the maximum regret case converge with VIKOR results when ν tends to 1, thus for *"risk-averse"* decision makers, as TOPSIS idiosyncrasy does so.

We conclude that the choice of MCDM method has little effect to the best performing policies; however, it can lead to different conclusions about the worst performing policies. Although the scope of this analysis is limited to distance-based methods, this showcases the merits of using a diverse set of MCDM approaches.

Despite the national scope of this study, results may be of relevance for policymakers of countries similar to Greece (e.g., in terms of variable renewable power generation potential). It is evident that designing policies aiming at green hydrogen diffusion should be done alongside provisions for storage capacity, toward reducing curtailment in grids and increasing the utilization of clean power generation. Otherwise,

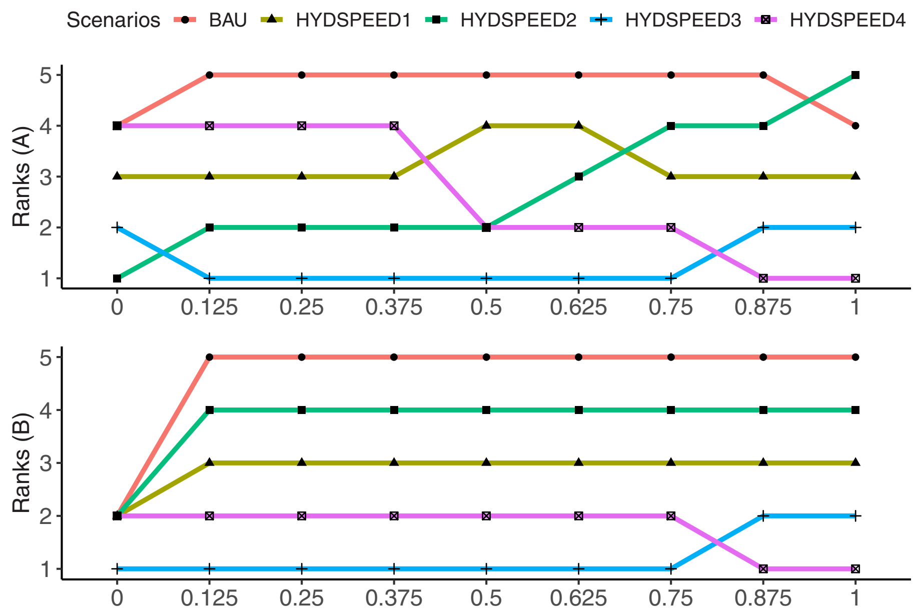

Fig. 7. Rankings of each policy scenario across ν coefficient values derived from VIKOR Q values, when uncertainty is treated, at the first stage, with the group utility metric S (A) and the maximum regret metric R (B).

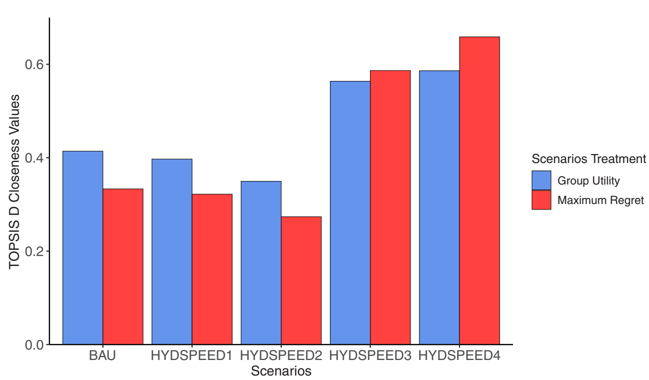

Fig. 8. TOPSIS D closeness values of policy scenarios to the optimal solution, when uncertainty is treated with the group utility metric S (blue colour bars) and the maximum regret metric R (red colour bars).

green hydrogen policies may lead to an increase of fossil fuels in power generation, which contradicts the motivation of a comprehensive green hydrogen strategy and may hinder the transition to net zero. It should be noted that higher utilization of green hydrogen storage would lead to lower reliance on more expensive renewables like geothermal as well as hydro, and thus to a less expensive green transition, with implications for land requirements and threats to biodiversity.

With regards to the intensity of introducing green hydrogen in the power sector, we find that there exists a turning point, up to which the preferences of decisions makers are better served with increasing rate of green hydrogen diffusion. This is mainly because the qualities of the energy system are improved in terms of total system capacity, import dependency, environmental performance, and variable costs, thereby counterbalancing the associated fixed costs and investments required. After this point, the observed trade-offs make further investments in green hydrogen less lucrative from the policymakers' perspective. Policies foreseeing a green hydrogen rate around the optimal point, however, also present higher uncertainty, compared to ones envisaging higher diffusion rates. Therefore, more conservative decision makers may choose to implement policies at which green hydrogen penetrates faster in the power sector, as these policies are less sensitive to uncertainties despite their lower marginal returns. It should be noted that the implications of our analysis regarding the preferable rates of green hydrogen diffusion could differ should alternative H_2 end-uses be considered; notably, the cost of the demand-side hydrogen-fueled technologies could increase the total cost of green hydrogen policies, thereby affecting the diffusion speed of choice. This is particularly relevant in sectors where electrification is the most cost-effective decarbonization option (e.g., road transport).

Fig. 9 presents the annual power generation per technology of the system over the 2030–2050 period across the examined green hydrogen policy scenarios.

As illustrated, wind and solar technologies dominate the energy mix towards 2050, at the expense of mainly natural gas and biomass, and to a smaller extent hydro. The increase in green hydrogen electricity storage alleviates the need for biomass-fueled electricity generation and, subsequently, the risk of harming ecosystems and their habitats [74,75]—a perspective that differentiates the power mixes of the examined green hydrogen policy scenarios from each other. Fig. 10 presents the average time profile of the produced green hydrogen across the time slices of the adopted modeling framework over the 2030–2050 period, for each of the examined green hydrogen strategies (Subplot A). As evident in this figure, at a monthly timescale resolution, hydrogen production increases in spring and summer months, alongside the capacity factors of the system's variable renewable generators (see Fig. 3), and the same can be observed from a daily time bracket perspective. These results are aligned with the rationale of deploying green hydrogen in power generation, i.e., transforming excess electricity into hydrogen, with a view to saving the excess energy in the form of hydrogen, thereby exploiting the merits of such storage type.

Furthermore, Fig. 10 illustrates the annual installed capacity of electrolyzers and fuel cells across the examined green hydrogen policy scenarios from 2030 to 2050 (Subplot B). This graph stresses the interconnected relationship between the expansion of hydrogen-based electricity storage and the capacity development of both electrolyzers and fuel cells. Notably, this demand is more pronounced for electrolyzers due to their lower load factor, which is closely tied to the intermittent nature of renewable power generation.

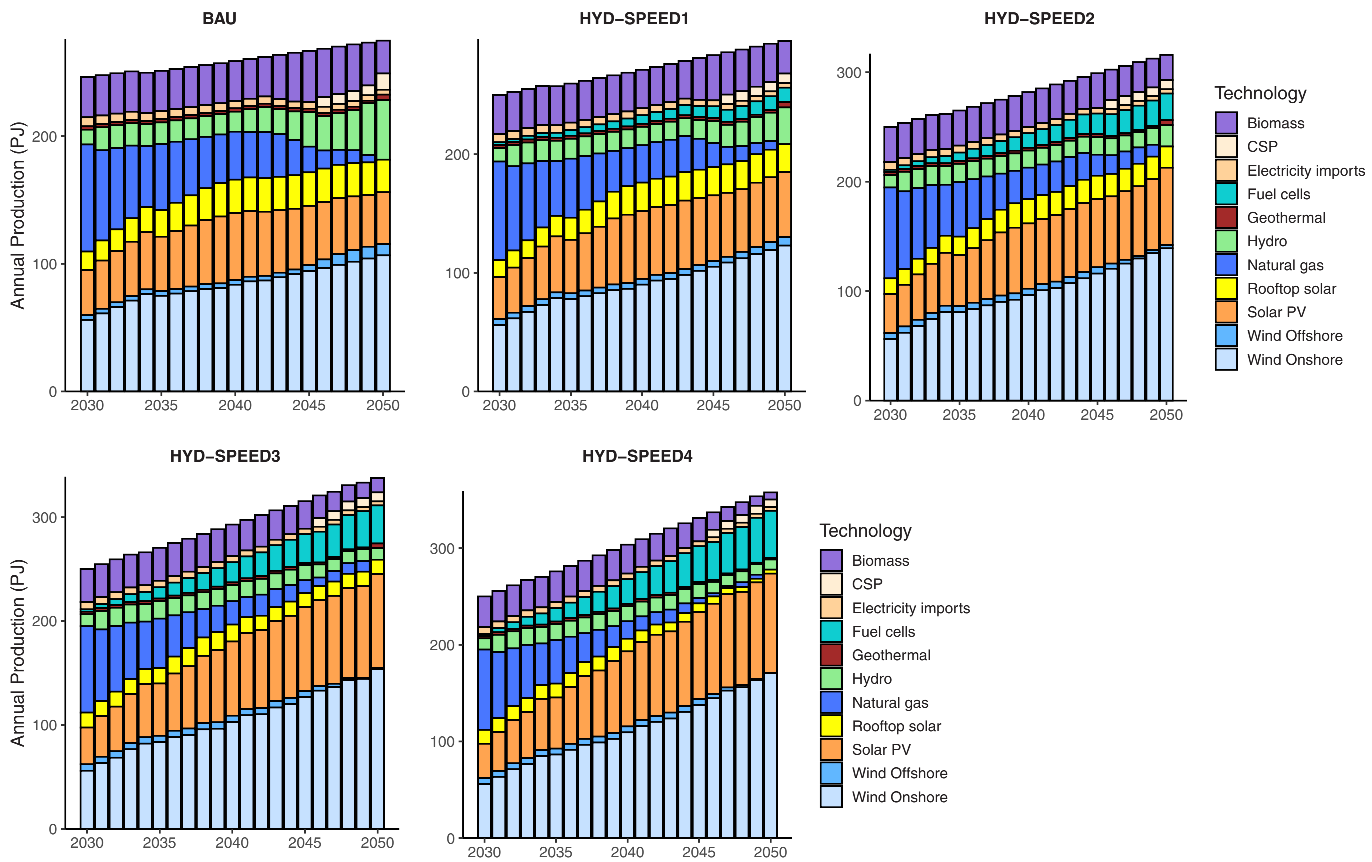

Fig. 9. Annual power generation per system technology over the 2030–2050 period across the examined green hydrogen policy scenarios.

5. Conclusions

Transitioning to carbon-free economies will require innovative technologies in power generation. In this study, we highlight the importance of the pace at which these technologies diffuse, considering various uncertainties and decision-making attitudes toward risk. We formulated policy scenarios of varying penetration speeds for green hydrogen in the Greek power sector and assumed different uncertainty scenarios regarding carbon pricing and electrolyzers efficiency. The power generation scenarios were simulated with OSeMOSYS-Greece to evaluate their robustness against uncertainty, using regret analysis. In turn, these scenarios were assessed with respect to environmental, economic, and technical criteria using two MCDM methods, VIKOR and TOPSIS. The divergent profiles of decision makers against uncertainty were modeled by different types of regret and MCDM methods.

We found that policies aiming for green hydrogen-powered electricity in the order of 15% of final demand by 2050 are deemed optimal, for policymakers that are either optimistic or neutral towards risk. These policies involve a gradual penetration of green hydrogen in Greece's power generation that reaches 53.41 PJ in 2050. To finance such policies, EUR 10 billion investments would be required, with the capital needed for the transformation of the entire Greece's power sector ranging at the level of EUR 31 billion over 2030–2050. Moreover, an increase of clean power capacity in the order of 6.6 GW would also be required, leading to almost 16 Mtn CO_2 of emissions cuts over 2030–2050.

In contrast, decision-makers with lower tolerance to risk may consider applying policies of higher diffusion rates, within which the green hydrogen-powered electricity could reach 20% of final demand in 2050. In this case, green hydrogen generation in the order of 71.22 PJ would be required by 2050, along with about EUR 12 billion of investments over 2030–2050. This amount, along with other investments that the green transition of Greece's power sector would necessitate, may reach the level of EUR 34 billion over 2030–2050. Moreover, an associated increase of clean power generation in the order of 7.3 GW would lead to almost 22 Mtn CO_2 emissions cuts over 2030–2050, compared to the zero green hydrogen case. Therefore, it can be concluded that green hydrogen can accelerate the transition of the Greek power sector at a relatively low economic cost.

Although not a panacea, green hydrogen can prove a game-changing option toward reaching net zero emissions targets. Although highly intertwined with the uptake of solar and wind technologies, its storage potential may prove key to handling associated challenges (e.g., land requirements, fossil fuel elimination, energy security, and costs), which—along with the investments that a green hydrogen economy can stimulate—are of vital importance to promoting societal acceptance of the required transformations [56], thereby increasing the success rates of energy and climate policies [76].

The study comes with a number of caveats, which can further motivate future research. First, direct hydrogen consumption is excluded from the analysis; in this respect, alternative uses of green hydrogen outside the power sector's scope (e.g., in transport [77]) can be examined instead—or in addition—allowing to determine a more holistic role of H_2 in transitioning to carbon-free economies. Moreover, there is no sensitivity analysis against the criteria weights used in the MCDM methods, as the focus has been on the type of regret, the MCDM method, and a key coefficient of one of the methods (VIKOR). OSeMOSYS-Greece can be further soft-linked with a macroeconomic model to evaluate the socioeconomic implications of the implied transition to a green hydrogen economy, which were not part of the scope and MCDM evaluation criteria of this study, as well as to deal with structural uncertainties of the OSeMOSYS framework. Finally, although

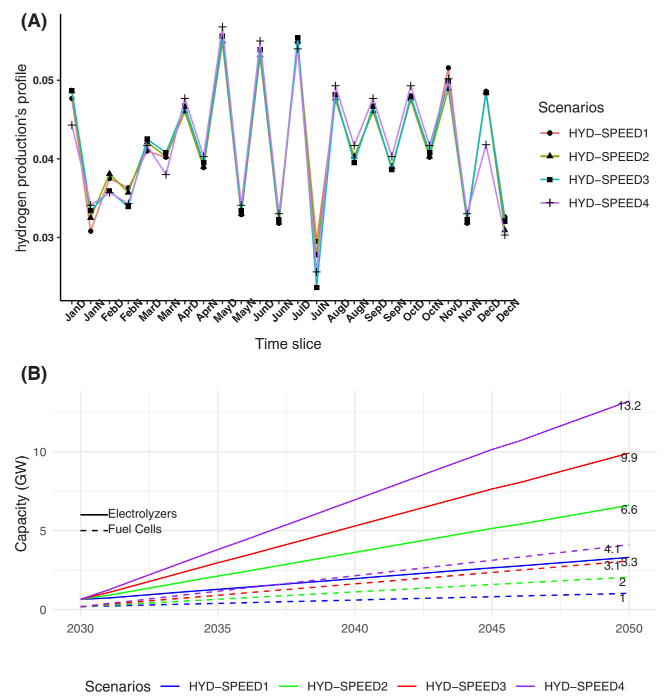

Fig. 10. (A) Average allocation of green hydrogen production across the time slices of the adopted modeling framework, over the 2030–2050 period. Naming of time slices arises from the first three letters of the entailed month and the letter D or N, for the day- and night-time bracket respectively; (B) Annual installed capacity for electrolyzers (solid lines) and fuel cells (dotted lines) over the 2030–2050 period across the examined green hydrogen policy scenarios.

TOPSIS was used to complement VIKOR in terms of risk behavior profiles, there are variants of the method that place risk behavior within the TOPSIS method itself [78] that can be used instead.

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CRediT authorship contribution statement

Diamantis Koutsandreas: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Georgios P. Trachanas:** Conceptualization, Methodology, Software, Validation, Data curation, Writing – original draft, Writing – review & editing. **Ioannis Pappis:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – review & editing. **Alexandros Nikas:** Conceptualization, Methodology, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Haris Doukas:** Conceptualization, Methodology, Writing – review & editing, Supervision, Project administration, Funding acquisition. **John Psarras:** Conceptualization, Methodology, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Alexandros Nikas reports article publishing charges was provided by Horizon 2020.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.esr.2023.101233.

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