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An investment evaluation and incentive allocation model for public-private partnerships in renewable energy development projects

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ABSTRACT

This study proposes an investment evaluation and incentive allocation model for public-private partnerships (PPPs) in renewable energy development projects (REDPs). A hybrid multicriteria decision-making (MCDM) and bi-level optimization model are proposed to evaluate investment opportunities and allocate government financial incentives (GFIs) to REDPs. The best-worst method (BWM) is used to weigh the evaluation criteria. VIKOR and grey relational analysis (GRA) rank and allocate GFIs to the private sector companies selected to participate in the REDPs. The government uses the PPP to persuade digital services companies in the private sector to invest in underdeveloped REDPs using financial incentives with minimal risk and maximum return. An iterative full-enumeration-based heuristic model is developed to handle the computational intractability in the bi-level model. The computational results show that *political and financial support* and *land use* are the most and the least important criteria, respectively. Moreover, we show that the government prefers to allocate a significant portion of its GFIs to *waste heat recovery* and *hydropower* in partnership with digital services companies. The results from the bi-level model help government agencies and policymakers offer equitable incentive programs in the energy sectors.

1. Introduction

Managing investments in renewable energy development projects (REDPs) is one of the most essential solutions to save energy and reduce environmental pollutants in low-carbon economies [1]. Many countries have invested heavily in establishing and developing renewable power plants in the last decade. Despite the efforts to manage investments, the shortage of financial resources has always been a significant problem for governments facing natural disasters, pandemics, and economic uncertainties [2]. Therefore, public sector budgets alone would not be sufficient to develop programs like REDPs. This has led governments to establish public-private partnerships (PPPs) to exploit REDPs.

Governments currently manage most REDPs in developing countries [3]. The private sector's willingness to be involved in these projects has encouraged governments to manage these financial support more effectively. This desire ignited the opportunity to make the most of private sector resources in achieving the goals of low-carbon economies (J. [4]). However, persuading the private sector to invest based on government strategies is challenging for most developing countries. Governments usually try to provide the necessary infrastructure for developing REDPs.

On the other hand, paying attention to the profitability of the private sector is considered a priority for many governments [5]. As a result, the private sector in most developing countries with poor economic infrastructure has little interest in REDPs because there is no guarantee of a reasonable rate of return on these investments [6]. For instance, the government's financial support for developing solar energy as a sustainable investment opportunity in Iran caused the private sector to increase its investment in solar power by 23 % in 2019 compared to 2016. However, inadequate government financial support decreased the private sector investment rate by 17 % in biomass and waste heat recovery energy, known as high-risk REDPs in Iran [7]. Therefore, governments must plan operational strategies to persuade the private sector to invest in high-risk REDPs.

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The energy consumption of digital services companies is growing at a rapid pace. For instance, blockchain, one of the most critical digital technologies, consumes enormous power. Nonetheless, blockchain development in the future is undeniable [8]. Having a reliable and sustainable energy resource to supply blockchain power is a critical problem in digital services companies [9]. Nair et al. (2020) show the rapid growth of research in the field. However, developing a renewable energy PPP is a win-win strategy for sustainable blockchain-based systems [10,11]. Therefore, this study proposes a hybrid multicriteria decision-making (MCDM) model and a bi-level optimization model within a PPP framework to evaluate investment opportunities in renewable energy. It is important to note that while this study specifically considers digital services companies, the proposed model can be adapted to accommodate other private investors, including traditional energy companies, based on the specific context and objectives of the PPP. This paper intends to provide a flexible methodology that can be applied across various private investor profiles.

Offering government financial incentives (GFIs), including no/low-interest loans, which reduce investment risk, is known as one of the most effective strategies for improving partnerships with the private sector in REDPs [12]). Optimal GFI allocation is among the critical problems for the government. If these resources are not effectively allocated, the results will not be effective, and the government will lose part of its investment. Despite the extensive research into renewable energy investment management, there is no integrated approach to prioritizing REDPs and providing optimal GFI for coordinating government and private sector decisions and developing renewable energy projects. The main research challenge is developing an efficient approach to evaluate renewable energy investment opportunities and optimally allocating GFIs to REDPs for successful PPPs.

This study develops a hybrid approach comprising the best-worst method (BWM), VIKOR, grey relational analysis (GRA), and a bi-level optimization model for evaluating investment opportunities and allocating GFI to REDPs. This approach is presented in two phases. Investment management and renewable energy development criteria are considered in the first phase based on research literature and experts' views. The obtained criteria are weighted using BWM. Then renewable energy projects, including solar, wind, biomass, hydropower, and waste heat recovery (WHR) alternatives, are prioritized by VIKOR and GRA. In the second phase, the optimal investment combination for the digital services companies and the optimal amount of allocated GFI to each alternative for the government is determined by solving a bi-level optimization model. In this model, the government provides financial incentives to digital services companies as private sector partners to invest in underdeveloped REDPs.

Considering that bi-level optimization models are strongly NP-hard [13], an effective full-enumeration-based heuristic is developed to solve the model. Finally, extensive numerical analysis is presented to evaluate the developed approach's applicability, the proposed method's performance, and the solution heuristic's effectiveness. Iran enjoys excellent potential to develop renewable energies because of its geographic situation. However, about 83.3 % of electric power is generated by fossil fuel and gas in heat, gas, combined cycle, and diesel power plants [14]. SABTA has presented some operational projects in recent years to extend renewable energy development infrastructure in cooperation with digital services companies. The contributions of this paper are summarized as follows.

- Evaluating investment opportunities in the field of renewable energies,
- An optimal allocation of GFIs to REDPs to motivate the digital services companies, as private sector investors, to cooperate in developing renewable energies,
- Designing a bi-level model to formulate the problem in a cooperative environment,
- Presenting an iterative full-enumeration-based heuristic to find the Stackelberg equilibrium,
- Applying the proposed approach to Iran's energy system as a case study in a developing country.

This paper refers to PPPs as a collaborative model between the public and private sectors to develop REDPs. PPPs in the renewable energy sector can take various contractual forms, each involving different degrees of risk transfer from the public sector to the private sector. Four main types of PPPs are ordered based on the level of risk transferred: 1) management and lease contracts, 2) brownfield projects, 3) greenfield projects, and 4) divestitures. These types encompass several subtypes, each presenting unique characteristics [15]. The proposed problem is designed to analyze PPP collaborations primarily in the context of Greenfield Projects (GP), which involve the development of new infrastructure or facilities from the ground up, typically in areas that have not been developed before (new sites or regions). The problem addresses undeveloped renewable energy projects, aligning with the concept of Greenfield Projects in the PPP classification. The government aims to increase investment in digital services companies in undeveloped renewable energy projects. This aligns with promoting investments in new and untapped areas, fitting the greenfield categorization. While the proposed methodology could be adapted for other PPP types, such as management and lease contracts or brownfield projects, its primary emphasis on encouraging investments in undeveloped renewable energy projects makes PGs the most suitable category. This ensures that the problem is aligned with the goal of fostering the development of renewable energy infrastructure in areas yet to be explored or exploited. It is important to note that the proposed methodology focuses on the strategic allocation of GFI to attract private investment, especially from digital services companies, in the context of renewable energy projects.

The remainder of the paper is structured as follows. Section 2 reviews the related criteria for evaluating renewable energy sources (RES) and different methods for REDP selection and GFI allocation. Section 3 presents the weighting and ranking methods framework in the MCDM phase and the proposed mathematical model and heuristic. Section 4 presents a case study of renewable energies in Iran. Section 5 reports the computational results of weighting the criteria, prioritizing the alternatives, and the related sensitivity analyses. The results of the optimization phase are then analyzed. Section 6 proposes the policy implications. Finally, the paper is concluded, and future suggestions are provided in Section 7.

2. Literature review

In this section, some of the related research is presented to establish the research gap. For this purpose, first, an overview related to the public-private partnership projects in renewable energy development is presented. Second, the main criteria for evaluating RES are presented. Finally, MCDM methods for selecting REDPs and optimization models for allocating the GFIs are investigated.

2.1. Public-private partnership projects in renewable energies development

PPPs have emerged as critical instruments for advancing renewable energy development on a global scale. This literature review offers a chronological narrative of key insights from research papers spanning various years, shedding light on the intricate dynamics of PPPs, government support, and renewable energy investment. Wang, Chen, Xiong, & Wu [16] conducted a study exploring the impact of contract characteristics on private investment in PPPs, specifically focusing on China's projects. The findings emphasized the positive association between private investment and competitive bidding, higher asset specificity, and increased residual rights controlled by private investors. These outcomes underscored the pivotal role of a competitive bidding process and collaborative structures to attract private investment in PPPs. Wang et al. [11,17]) delved into the relationship between government support programs and private investments in PPP markets across 130 developing countries Wang et al. [11,17,18]). The study revealed the positive impact of direct government support (subsidies) on attracting private capital, highlighting the importance of institutional quality and risk allocation. This research provided valuable insights into crafting effective government policies to stimulate private investments in PPPs.

Yang, Huo, Saqib, & Mahmood [19] conducted an investigation into the relationship between renewable energy, PPPs, and carbon emissions, testing the Environmental Kuznets Curve (EKC) hypothesis. The findings highlighted the mitigating effect of renewable energy on CO2 emissions, particularly in lower and upper quantiles. The study recommended increased government investment in renewable energy and PPPs, aligning with environmentally friendly practices. Kirikkaleli, Ali, & Altuntaş [20] focused on the impact of PPP investment in energy on CO2 emissions in Bangladesh. The study revealed a long-term association among PPP investment, economic factors, and CO2 emissions. Economic growth and PPP investments increased environmental degradation, with mitigation provided by renewable energy and financial development. Akinsola et al. [21] explored the relationship between PPP investment, financial development, and ecological footprint in Brazil. The research employed various econometric techniques, revealing that economic growth and PPP investments increased environmental degradation, with mitigation provided by renewable energy and financial development. Chileshe, Njau, Kibichii, Macharia, & Kavishe [22] investigated critical success factors (CSFs) for PPPs in infrastructure and housing projects in Kenya. The study identified key CSFs, including community support, project feasibility, legal frameworks, and financial market availability. These findings offer practical insights for successful PPP implementation in the Kenyan construction sector. Xie, Zhao, Chen, & Allen [23] delved into green supply chain management within the construction industry [23]. The study advocated for governmental intervention and PPPs to foster ecological modernization. Coordination between government support and PPPs was highlighted as necessary for achieving environmental and economic performance benefits in the construction sector. Basílio [24] examined the role of Multilateral Development Banks (MDBs) in supporting renewable energy projects, particularly in the context of the Paris Climate Agreement [24]. The study underscored MDBs' active involvement in climate finance while raising questions about the alignment of support with renewable energy goals. This research signaled the need for increased financial backing to reinforce MDBs' commitments to clean energy.

The literature review presents a practical understanding of the factors influencing the success of PPPs in renewable energy projects. It underscores the importance of aligning government policies, fostering community financial support, and strategically implementing green technologies. This synthesis provides a foundation for developing an investment evaluation and incentive allocation model that integrates the complexities of PPPs in the renewable energy sector. Future research and policy efforts should leverage these insights to enhance the effectiveness and sustainability of PPPs in advancing renewable energy initiatives globally.

2.2. The related criteria for evaluating RES

There are many criteria to be studied in the literature in the field of RES selection. These criteria are primarily categorized into five economic, technical, managerial, environmental, and social criteria [25].

Economic criteria: This measure is essential to decision-making processes since managers tend to utilize the solutions with the minimum overall cost. This criterion has some sub-criteria, including investment cost [26], operation and maintenance (O&M) cost [27], production cost [28], and investment payback period [29].

Technical criteria: REDPs have specific technical guidelines that directly affect their success [30]. The most critical related sub-criteria are efficiency, production capacity, and technological development [31].

Managerial criteria: There are two crucial sub-criteria for managing REDPs, according to the literature: (1) political and financial support and (2) compatibility with the national energy political plan [32]. Considering these sub-criteria can increase the success of the projects.

Environmental criteria: The process of carrying out REDPs has remarkable environmental effects. Based on the literature, one of the leading environmental criteria is that greenhouse gas (GHG) emissions have adverse global and regional results on ecosystems. Moreover, constructing renewable energy systems requires suitable land. Local communities have to allocate some space to REDPs that could be used for other potential goals like farming [33]. Therefore, land use should be mainly considered [34].

Social criteria: It is vital to aggregate people's final opinions about launching different renewable energy systems because people are the primary beneficiaries of renewable energies. In addition, employment opportunities created by REDPs can, directly and indirectly, impact people's lives [33]. Finally, job creation [31] and social acceptance [26] can be considered among the leading social criteria.

2.3. MCDM and optimization methods

In the literature review, the problem of investment opportunity evaluation in renewable energies is investigated as the prioritization of renewable energy alternatives. Therefore, this sub-section focuses on the research related to RES ranking.

MCDM methods have a wide application in the literature for evaluating RES. Several studies used the analytic hierarchy process (AHP) to weight the related criteria [35,36]; Wang et al. [11,17,25]. Analytic network process (ANP) and Shannon's entropy are the other weighting methods that have been used in a few studies ([37]; Y. [38]).

Different MCDM techniques are used to prioritize alternatives [39]. Lee & Chang [37] presented a comparative analysis of the weighted sum method (WSM), VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), the technique for order of preference by similarity to ideal solution (TOPSIS), and ÉLimination et Choix Traduisant la REalité (ELECTRE) for prioritizing renewable energy sources in Taiwan. Büyüközkan & Güleryüz [33] applied decision-making trial and evaluation laboratory (DEMATEL), ANP, and TOPSIS for the evaluation of RES in Turkey. Based on their results, the best renewable energy technologies in Turkey are geothermal and biogas power. Çolak & Kaya [40] prioritize renewable energy alternatives in Turkey by fuzzy-AHP and TOPSIS. About the new MCDM methods [41,42], investigated the problem of evaluating RES using BWM. Based on the authors' best knowledge, there is no other research to use the new MCDM method in this field; however, new MCDM techniques like BWM have been used widely in different areas of renewable energy development [43]. Table 1 shows some of the main studies related to evaluating renewable energies.

Although the allocation of government incentives has a critical role in improving the cooperation between government and digital services companies in the field of renewable energy investment, there is no research in the literature to investigate this problem from operation and decision-making perspectives. However, GFIs have been allocated to other fields, such as cooperation supply chain design [71]. Therefore, using mathematical programming, this study can be considered the first to investigate investment opportunity evaluation and governmental incentive allocation in renewable energies.

3. Proposed approach

The proposed approach is described in two phases. First, the framework of BWM as a weighting method and VIKOR and GRA as ranking methods are explained in the MCDM phase. Second, the bi-level mathematical model and the heuristic algorithm are presented in the optimization phase.

Table 1
Main studies in the field of renewable energy evaluation.

Ref.	MCDM methods										Criteria				
	Weighting method				Alternative prioritization method										
	EWA	ANP	AHP	BWM	AHP/ANP	T	V	G	P	E	EC	TE	MA	EN	SO
[40]			✓			✓					✓	✓	✓	✓	✓
[44]			✓		✓						✓	✓		✓	✓
[33]		✓				✓					✓		✓	✓	✓
[42]				✓		✓					✓	✓	✓	✓	
[45]	✓					✓					✓			✓	✓
[46]			✓			✓	✓				✓			✓	✓
[1]			✓			✓					✓		✓	✓	✓
[37]	✓						✓		✓	✓	✓	✓	✓	✓	✓
[47]	✓									✓	✓			✓	✓
[48]			✓			✓					✓			✓	✓
[36]			✓			✓					✓	✓		✓	✓
[26]		✓			✓						✓		✓	✓	✓
(Y. [38])		✓			✓						✓	✓		✓	✓
[41]				✓		✓					✓	✓		✓	✓
[49]			✓		✓						✓			✓	✓
[50]	✓					✓	✓		✓		✓	✓		✓	✓
[51]			✓					✓			✓	✓	✓		✓
[52]			✓			✓					✓	✓		✓	✓
[53]	✓						✓				✓	✓		✓	
[54]	✓					✓					✓			✓	✓
(Y. [25])			✓		✓						✓	✓		✓	✓
[10,11]			✓				✓				✓		✓		
[55]		✓			✓						✓	✓		✓	
[56]	✓					✓					✓			✓	✓
(M. [57])	✓				✓						✓	✓	✓	✓	✓
(W. [58])			✓						✓		✓	✓	✓	✓	
[59]		✓				✓					✓			✓	✓
[60]	✓								✓		✓		✓		
[61]	✓								✓		✓			✓	
[62]		✓						✓			✓	✓			
(M. [63])		✓					✓				✓		✓	✓	✓
[64]	✓					✓					✓	✓		✓	✓
(H. [65])	✓				✓	✓					✓	✓	✓	✓	
[66]	✓								✓		✓		✓	✓	✓
[67]			✓		✓			✓			✓	✓		✓	
[68]		✓							✓				✓		✓
(Z. [69])	✓				✓						✓		✓	✓	
[70]	✓				✓						✓		✓	✓	
This study			✓	✓			✓	✓			✓	✓	✓	✓	✓

EWA: entropy-weighting approach; **DE:** DEMATEL; **T**: TOPSIS; **V**: VIKOR; **G**: grey relational analysis;
P: PROMETHEE; **E**: ELECTRE; **EC**: Economic; **TE**: Technical; **MA**: Managerial; **EN**: Environmental; **SO**: Social.

3.1. MCDM phase

This phase weighs the related criteria to investment management and renewable energy development by BWM and prioritizes REDPs using VIKOR and GRA. First, economic, technical, managerial, environmental, and social criteria are obtained from literature and experts' views. Then, BWM is applied to determine the global weight of these criteria/sub-criteria. Finally, a numerical analysis is presented to evaluate GRA and VIKOR sensitivity from robustness insight. Fig. 1 illustrates the framework of the proposed MCDM phase.

3.1.1. The advantage of applying BWM, VIKOR, and GRA

AHP, ANP, BWM, and other similar methods have been applied to obtain the criteria weights in MCDM problems [72,73]. Several comparisons should be made between AHP and ANP [74]. However, BWM requires fewer ones [75]. Let's consider an MCDM problem with n decision criteria, then AHP and BWM will respectively require $n(n-1)/2$ and $2n-3$ comparisons [76–78]. Moreover, BWM obtains the criteria weights by a mathematical model, and the solutions are global optimal and consequently more reliable. In contrast, the final results of AHP and ANP can be affected by the personal preferences of different experts [77]. Second, GRA is one of the most used methods in solving problems, especially business problems, with simple and understandable calculations (H.-H. [79]). S.-f. Zhang, Liu, and Zhai [80] showed that the results obtained from GRA are highly stable. Finally, regarding applying VIKOR, Opricovic [81] stated that the final results of VIKOR are compromised regarding distance to the ideal solution.

Overall, it is hard to claim which method is more reliable. One approach is to compare the results of different methods [82]. This study performs a sensitivity analysis to compare the performance of VIKOR and GRA.

3.1.2. Best-worst method

BWM is among the recent MCDM techniques first designed by Refs. [77,78]. This method consists of reference comparisons and has fewer calculations than AHP and ANP. Fig. 2 shows the BWM flowchart. Moreover, the steps of BWM are described in the Online Resources section in detail.

3.1.3. Grey relational analysis

Deng [83] proposed GRA, which is based on the concept of grey systems theory. A kind of distance measurement is used to determine the relationship between alternatives. Fig. 3 shows the GRA flowchart. Moreover, the steps of GRA are described in further detail in the Online Resources.

3.1.4. VIKOR technique

VIKOR is a powerful MCDM method with compromise solutions

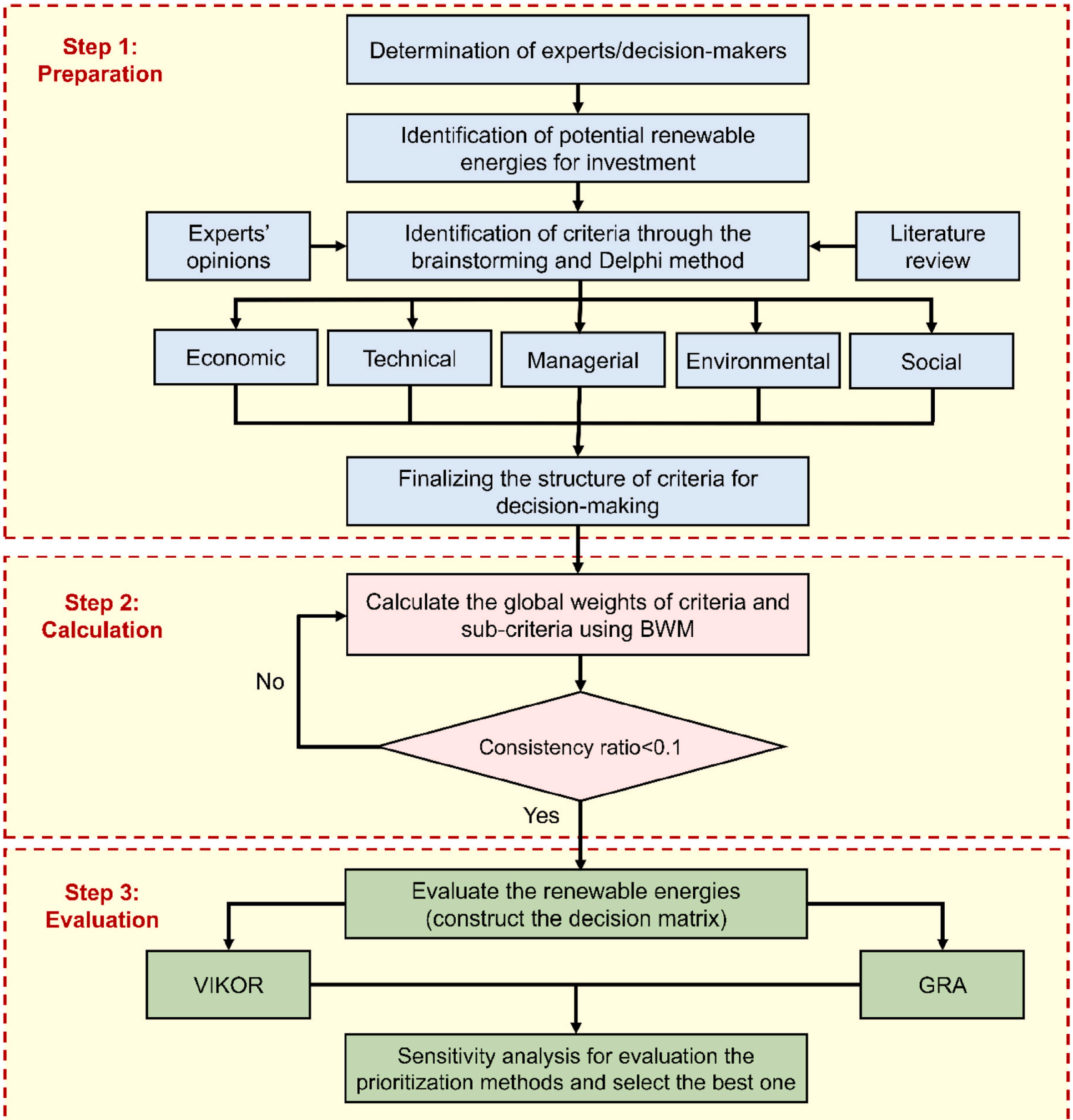

Fig. 1. Flowchart of the proposed MCDM phase.

obtained based on closeness to the ideal solution [81]. Fig. 4 shows the VIKOR flowchart. Moreover, the steps of VIKOR are described in further detail in Online Resources.

3.2. Optimization phase

The selection of investment projects related to renewable energies is among the complex management decisions that need to be solved using optimization models, including mathematical modeling [84]. Investing in REDPs should be managed based on government strategic plans and private sector preferences. In other words, there are two decision-makers in the optimization phase. This paper uses a bi-level optimization model to optimally solve the GFI allocation problem. Fig. 5 shows the flowchart of the optimization phase.

The government allocates GFI to REDPs in the proposed bi-level model to increase investment in digital services companies in undeveloped renewable energy projects. For this purpose, the minimum investment in REDPs in digital services companies is maximized by allocating GFI at the upper level. A multi-objective model is designed to determine investment in digital services companies based on the rate of return and investment risk of projects. The proposed mathematical

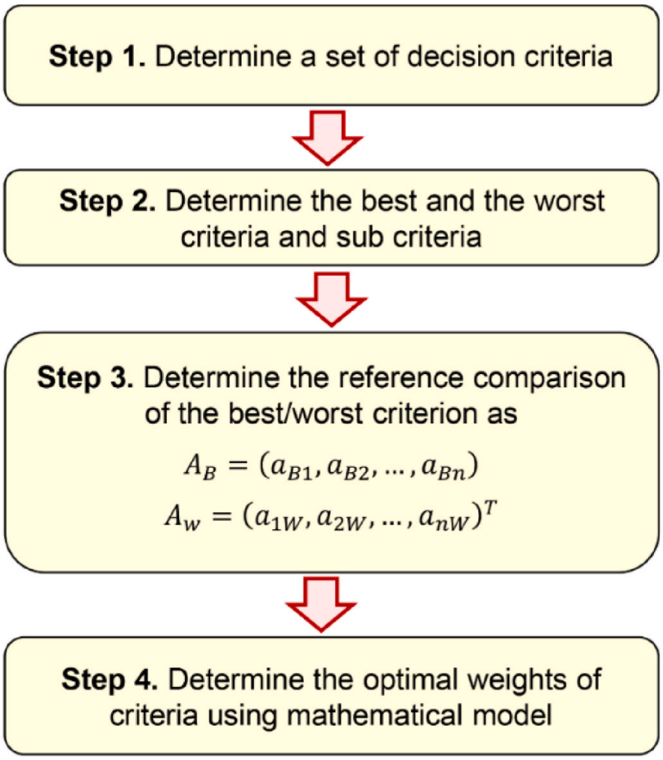

Fig. 2. Bwm flowchart.

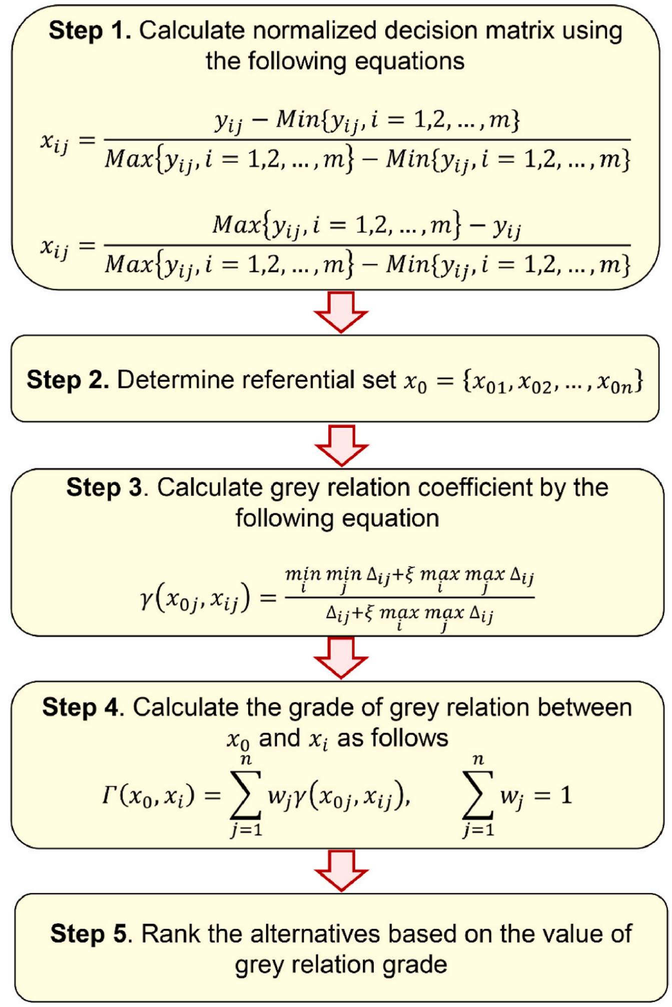

Fig. 3. Gra flowchart.

formulation is presented as follows.

Sets and indexes	
$i \in \{1, \ldots, I\}$	Set of renewable energies (index i)
Government parameters	
P_i	Development preference of renewable energy projects i
L_i	The government's lower bound on investing in renewable energy i
U_i	The government's upper bound on investing in renewable energy i
Budget	The total available budget for REDPs
Private sector parameters	
$Income_i$	The annual income from investing in renewable energy i
$cost_i$	Cost of investing in renewable energy i
β_i	Risk of investing in renewable energy i
F_i	Private sector company's lower bound on investing in renewable energy i
K_i	Private sector company's upper bound on investing in renewable energy i
N	Maximum number of REDPs for investing
M	A positive and large enough number
Government decision variables	
y_i	The amount of allocated GFI to REDP i
Z	Minimum investment in REDPs by the digital services companies
Private sector company (follower) decision variables	
x_i	The amount of investment in REDP i
w_i	Equal to 1 if REDP i is selected for investing by the private sector company; otherwise, 0.

Government model

$$Max\ Z \tag{1}$$

s.t.

$$Z \le P_i \times x_i \tag{2}$$

$$L_i \le x_i \le U_i \quad i \in I \tag{3}$$

$$\sum_{i \in I} y_i = Budget \tag{4}$$

$$y_i \le M \times w_i \quad i \in I \tag{5}$$

$$w_i \le M \times y_i \quad i \in I \tag{6}$$

$$y_i \ge 0\ x, w \in U^*(y, Z) \quad i \in I \tag{7}$$

Private sector company (follower) Model

$$Max\ Z_1 = \sum_{i \in I} \left(\frac{(Income_i + y_i)}{cost_i} - 1 \right) \times x_i \tag{8}$$

$$Min\ Z_2 = \sum_{i \in I} \beta_i \times x_i \tag{9}$$

s.t.

$$\sum_{i \in I} x_i = 1 \tag{10}$$

$$F_i \le x_i \le K_i \quad i \in I \tag{11}$$

$$\sum_{i \in I} w_i \le N \tag{12}$$

$$w_i \in \{0, 1\}\ and\ 0 \le x_i \le 1 \quad i \in I \tag{13}$$

The government's objective function (1) is to maximize the minimum investment of the digital services companies in REDPs. According to Equation (2), variable Z calculates the minimum amount of private-

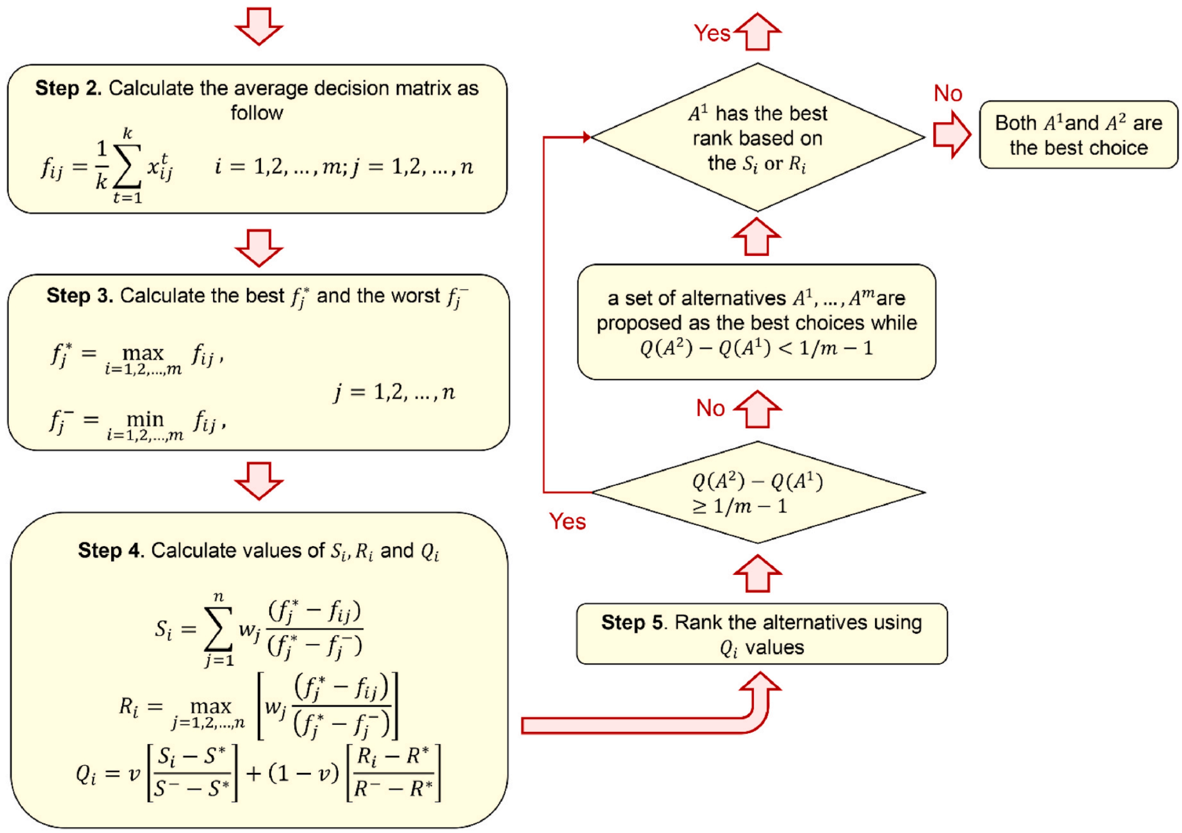

Fig. 4. Flowchart of VIKOR.

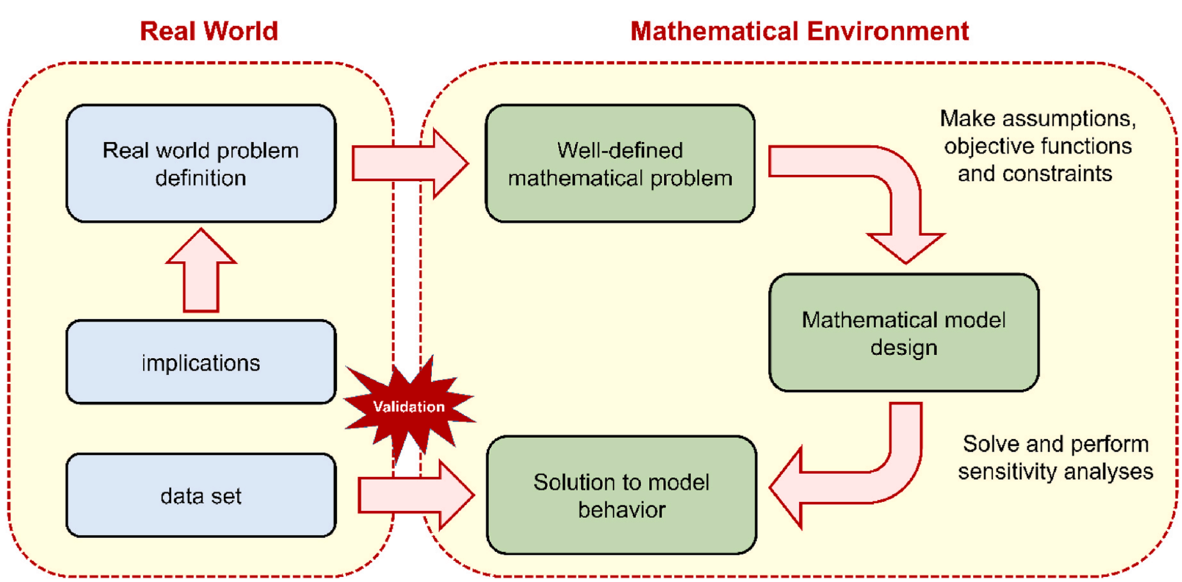

Fig. 5. Flowchart of the proposed optimization phase.

sector investment. In this model, the assumption has been made that all private partners share the same conditions and are regarded uniformly by the government in terms of value. Equation (3) guarantees that the private sector company's investment should be in the pre-determined interval by the government. Equation (4) ensures that the total investment for all REDPs should equal the total budget. According to Equations (5) and (6), GFI can be allocated to a REDP, which the private sector company selects for investing. Equation (7) shows the domain of decision variables of leader model and also clarify x_i, w_i are determined by solving follower model optimally with considering y_i, Z. In this constraint, the set $U^*(y_i, Z)$ is a set of optimal solutions of the follower level problem.

In the private sector company model, the first objective function (8) maximizes the annual return rate for the selected REDPs. In this model, it is assumed that all GFIs can be converted as cash incentives form. The second objective function (9) minimizes the total risk of the chosen REDPs. It should be noted that the project risk is calculated based on the geometric mean deviation from the stock return rate of energy companies in the stock market. Equation (10) guarantees that the total investment portion in the selected REDPs should equal 1. Equation (11) ensures that the investment portion for private sector companies in each REDP should be in the pre-determined interval by the government. Equation (12) guarantees that the maximum number of selected REDPs for investing equals *N*.

3.2.1. Solution method

This paper proposes an iterative full-enumeration-based heuristic to solve the bi-level model near-optimally. Since the proposed heuristic solves the model based on a unique solution of the private sector company, the goal attainment method (GAM) is used to convert the private sector company model to a single-objective model to obtain a unique solution instead of the Pareto front.

3.2.1.1. Goal attainment method (GAM). GAM is an efficient method of finding the best compromise solution in multi-objective problems (Y.-L. [85]). In this method, weighted vectors of v_1 and v_2 should be determined by decision-makers with the aim of defining the importance of each objective function. Then, for each objective, the minimum distance from its optimal value is calculated using Equations (14) to (16).

$$Min\ G \tag{14}$$

$$s.t.$$

$$Z_1^* - Z_1 \le v_1 G \tag{15}$$

$$Z_2 - Z_2^* \le v_2 G \tag{16}$$

where, v_1 and v_2 are defined as technical weights so that $v_1 + v_2 = 1$. Based on the definitions, the private sector company model can be converted into a single-objective one as Equations (17) to (20).

Single-objective private sector company model

$$Min\ Z_3 = G \tag{17}$$

$$s.t.$$

$$Z_1^*(y) - \sum_{i \in I} \frac{(Income_i - y_i) - cost_i}{cost_i} \times x_i \le v_1 G \tag{18}$$

$$\sum_{i \in I} \beta_i \times x_i - Z_2^* \le v_2 G \tag{19}$$

Constraints (10) to (12)

$$G \text{ is unrestricted in sign} \tag{20}$$

Equation (17) minimizes the distance of objective functions from their optimal values. Standardization is not required since the numerical interval of objective functions is similar, and the *G* value is valid for the two objective functions. Equations (18) and (19) calculate the weighted distance of the objective functions from their optimal values. Constraints (10) to (12) means to consider the constraints of the leader model. Equations (20) indicate that variable *G* is free in the sign.

The follower model is solved based on the given values in the leader model and y_i is assumed as a parameter in the follower model. Therefore, Constraint (7) should be modified as Constraint (7 M), as follows:

$$y_i \ge 0\ (G, x, w) \in U^*(y, Z)\ \ i \in I \tag{7M}$$

The final formulation of the bilevel problem solved in this paper will be as follows: (1)–(6), (7 M), (17), (18), (19), (10)–(13), and (20).

Based on the proposed solution method explained in subsection b in section 3.2.1.2, the follower model should be solved for all generated strategies of the leader model. Therefore, in each iteration of the solving procedure of the follower model, there are fixed values for the variable y_i. In this situation, $Z_1^*(y_i)$ can be obtained, and the single-objective private sector company model can be solved.

3.2.1.2. Iterative full-enumeration heuristic algorithm (IFEH). Addressing bi-level models, mainly when a discrete variable is present at the private sector company level, poses a significant challenge within operations research (Gao et al., 2005). This study introduces the IFEH algorithm as a novel approach to tackle this longstanding open problem. The essence of the IFEH algorithm lies in its utilization of all feasible solutions of the government as initial solutions. In each iteration, the government formulates strategies communicated to the private sector company through the generated feasible solutions. The private sector company, in turn, identifies and retains optimal solutions corresponding to each strategy proposed by the government, forming the Government's Strategies Set (GSS). Subsequently, the private sector company leverages the GSS to present its optimal solution. This solution set is then integrated into the government model, and the objective function *Z* is computed within the framework of the government-level model. The solution yielding the optimal value for the government is designated as the final solution from all the obtained solutions. The operators are delineated as subsections (I) to (III) to delve further into the mechanics of the IFEH algorithm. This comprehensive approach advances the understanding of bi-level models and provides a practical algorithmic solution to a persistent challenge in operations research.

3.2.1.3. Applicability of the IFEH algorithm. The IFEH algorithm exhibits notable applicability in addressing intricate challenges inherent in bi-level models, especially those featuring discrete variables at the private sector company level. The algorithm's utility is elucidated through several key aspects.

3.2.1.3.1. Handling discrete variables. Bi-level models incorporating discrete variables present a formidable computational challenge. The IFEH algorithm is expressly designed to navigate this complexity by introducing a systematic approach. It utilizes all feasible government solutions as initial solutions, systematically addressing the nuances introduced by discrete variables.

3.2.1.3.2. Iterative solution refinement. The iterative nature of the algorithm is a distinguishing factor. The government proposes strategies to private sector companies through each iteration based on the feasible solutions generated. This iterative process fosters a nuanced exploration of the solution space, enhancing the algorithm's capability to converge toward optimal solutions over successive iterations.

3.2.1.3.3. Government-private sector company interaction. A fundamental feature of the IFEH algorithm lies in the dynamic interaction between the government and the private sector company. The government's strategic proposals guide the private sector companies in generating optimal solutions. This collaborative approach facilitates a mutual exchange of information and enriches the understanding of the problem landscape from both perspectives.

3.2.1.3.4. Government's Strategies Set (GSS). The introduction of the GSS is a pivotal concept in the algorithm. This set consolidates optimal solutions corresponding to various government strategies, serving as a comprehensive repository. The GSS streamlines the presentation of optimal solutions by the private sector company, contributing to the efficiency and effectiveness of the algorithm.

3.2.1.3.5. Integration and final solution determination. The algorithm's methodology extends to integrating optimal private-sector company solutions into the government model. Following this integration, the objective function *Z* is computed at the government level. The determination of the final solution, grounded in the government's perspective, underscores the holistic nature of the IFEH algorithm, ensuring a robust and well-considered outcome.

3.2.1.4. Strategy generation for the government. GSS is considered the set of initial heuristic solutions; therefore, it is necessary to design a systematic procedure to explore more efficient leadership strategies to improve the algorithm performance. For this purpose, an iterative technique is developed in such a way that, if there is $\{1, \ldots, |I|\}$

Strategies and members of this set can be calculated using Equation (21).

$$LSS = \left\{ \binom{|I|}{i}, i \in \{1, \dots, I\} \right\}$$
$$|LSS| = \sum_{i \in \{1,\dots,I\}} \binom{|I|}{i} \tag{21}$$

For instance, if three types of REDPs are available, GSS is generated as Equation (22).

$$LSS = \{(1), (2), (3), (1,2), (1,3), (2,3), (1,2,3)\}$$
$$|LSS| = \binom{3}{1} + \binom{3}{2} + \binom{3}{3} = \frac{3!}{2!} + \frac{3!}{2!} + 1 = 7 \tag{22}$$

If there are three REDPs, the government will have seven different strategies. Given that the private sector company model is solved quickly via commercial solvers, generating government strategies to allocate GFIs to REDPs will be possible. There is a challenging problem in the strategy generation procedure to determine the amount of GFI for each GSS member because $y_i \in \mathscr{R}^+$. Therefore, there are unlimited feasible combinations of y_i for each strategy. In this paper, a local search algorithm is proposed to find efficient combinations of y_i based on the government's objective function as an efficiency measure and the private sector company's objective function as a fitness function.

3.2.1.5. Local search algorithm for GFI allocation. In this paper, a local search algorithm is developed to determine efficient combinations of y_i for GSS members. In this algorithm, an array with a length of $|LSS|$ is considered and called Y_{si}, where in each cell of Y_{si} a random number in [0,1] is generated based on a constraint that guarantees $\sum_i Y_{si} = 1$. Then, two neighbor solutions are generated by Equations (23) and (24).

In these equations, i is the index of set of renewable energies and $s \in \{1, \dots, |LSS|\}$. However, the index i should be aligned with the index s. In fact, the index i counts the members of LSS. For example, for a subset of LSS like {1,2,3}, the index i shows the 1,2, and 3. Also, for another subset of LSS like {2,3}, the index i shows the 2 and 3.

$$W_{si}^{+} = Y_{si} + C \times (u_{si} - v_{si}) \tag{23}$$

$$W_{si}^{-} = Y_{si} - C \times (u_{si} - v_{si}) \tag{24}$$

where $C \sim N(\mu, \sigma^2)$ is considered as a perturbation factor, u_{si} and v_{si} are two randomly selected members. It is clear that if $\sum_i W_{si}^{+} \neq 1$ and $\sum_i W_{si}^{-} \neq 1$, a repair strategy is needed to set them equal to 1. If σ and μ have large values, the perturbation factor will have an excessive effect on the population generation procedure so that the heuristic convergence will deviate. Based on the experiments, it is recommended that these parameters should be generated in the interval [0,1]. In the next step, the fitness value of each developed solution is calculated using the private sector company's objective function to replace it in the next generation based on **Pseudocode 1**.

Pseudocode 1. replacement strategy

```
If fitness(W+_si) < fitness(Y_si) AND fitness(W-_si) < fitness(Y_si)
    Randomly choose one to replace Y_i
If fitness(W+_si) < fitness(Y_si) OR fitness(W-_si) < fitness(Y_si)
    Y_si is replaced by the one that dominates it
Else
    Y_si is selected for next generation
End if
```

Where the *fitness()* function is calculated based on the private sector company objective function; thus, the optimal combination of GFI allocation to the selected REDFs is determined. The pseudocode of the local search algorithm is presented as **Pseudocode 2**.

Pseudocode 2. local search algorithm

```
For s=1 in S = {1, ..., |LSS|}
    For i=1 in {1, ..., |I|}
        Calculate C~N(μ, σ^2);
        Choose two members u_si and v_si randomly from the population.
        Generate two neighborhood solution W+_si and W-_si by Equations (38) and (39), respectively.
        Replace Y_si using the proposed replacement strategy.
    End For
End For
```

To clarify the selection process of u_{si} and v_{si}, it should be mentioned that each member of S which is shown by the index s, contains a group of energies which are shown by i. For example, $s = 5$ may include a group of energies like $\{1, 2, 3, 4, 5\}$. This group can be considered as a population in which u_{si} and v_{si} are selected from that.

Based on the mentioned steps, the set of feasible government strategies, including the selected REDPs and the optimal amount of allocated GFIs, are generated using GSS and a local search algorithm. According to these strategies, the private sector company model is solved optimally for each developed feasible government strategy to create a feasible solution space for the government. Consequently, the final solution of the heuristic is proposed to the decision-makers by replacing the obtained private sector company decision variables for each strategy in the government model and calculating the best value according to the government's objective function.

The proposed heuristic considers a classical non-cooperative Stackelberg game from the game theory perspective. The government maximizes the minimum investment in the digital services companies (or private sector) in REDPs, and the private sector company tends to maximize its annual rate of return for the selected REDPs and minimize the total risk of the selected REDPs in a competitive environment. In each iteration of IFEH, the private sector company's optimal solutions are calculated according to the feasible strategies the government generated. In this way, the Stackelberg equivalent can be obtained near-optimally. This approach best solves the bi-level models where the private sector company level has discrete variables [71].

3.2.1.6. Limitations of the IFEH algorithm. While the IFEH algorithm presents a promising approach to addressing challenges in bi-level optimization, it is essential to recognize certain limitations that may impact its applicability and performance.

3.2.1.6.1. Computational intensity. The iterative nature of the algorithm, involving repeated interactions between the government and private sector companies, may result in increased computational intensity. The algorithm's performance could be impacted when applied to large-scale problems, particularly those with a high dimensionality of decision variables.

3.2.1.6.2. Sensitivity to initial solutions. The reliance on all feasible government solutions as initial solutions might make the algorithm sensitive to the quality of these initial solutions. In scenarios where the government's feasible solutions are not well-distributed or representative, the algorithm's convergence to optimal solutions may be hindered.

3.2.1.6.3. Discretization challenges. Handling discrete variables, although a strength of the algorithm, can also be a limitation. The algorithm's effectiveness may be contingent on the nature and distribution of discrete variables, and it might face challenges in cases where discrete decision spaces are highly fragmented or involve intricate combinatorial structures.

3.2.1.6.4. Limited Adaptability to dynamic environments. The IFEH algorithm's performance may be compromised in dynamic optimization environments where the problem parameters or constraints undergo frequent changes. The algorithm's iterative nature might struggle to adapt to evolving scenarios promptly.

3.2.1.6.5. Lack of robustness to noisy data. The algorithm may exhibit reduced robustness in noisy or uncertain data. Variability or inaccuracies in the input data could lead to suboptimal solutions or hinder the algorithm's convergence.

3.2.1.6.6. Solution interpretability. The complexity introduced by the iterative interactions and the integration of optimal private-sector company solutions into the government model may render the final solution less interpretable. Understanding the underlying decision-making process might be challenging, limiting the algorithm's transparency.

Table 2
Related information about active companies in renewable energies in Iran.

Power plant	Nominal Capacity MW	Installed Capacity MW	Number of companies
Wind	1427	302	45
Solar PV	2685	365	299
Biomass	31	11	5
Small Hydropower	15	91	8
Waste heat recovery	68	13	5
Total	**4226**	**782**	**362**

3.2.1.6.7. Algorithm tuning requirements. Achieving optimal performance with the IFEH algorithm may require careful tuning of parameters, making it sensitive to the choice of algorithmic settings. This tuning process can be time-consuming and may necessitate domain-specific expertise.

4. Case study

This paper investigates the evaluation of investment opportunities and governmental incentive allocation in renewable energies in Iran as a case study. Fig. 6 illustrates the trend of electricity generation using renewable resources and the portion of renewable energies to total generated energy in Iran from 2001 to 2019.

Providing financial resources for REDPs is one of Iran's most challenging problems. Iranian banks as investment institutions cannot completely cover the required financial resources for REDPs and provide high-interest loans (about 18 % interest rate). Moreover, the recent decline in oil price, as the primary income of Iran, makes the government prioritize industrial projects to pay them from the limited National Development Fund [86].

According to the proposed information on the SABTA website [87], nominal capacity, installed capacity, and the number of active companies in the renewable energy section by the end of 2019 are presented in Table 2.

According to Table 2, by the end of 2019, about 46.6 % of electricity generation in the renewable energy sector is related to solar energy. 38.6 % of the electricity is generated by wind energy, and other renewable energy power plants produce 14.8 % of the electricity. Moreover, the nominal capacity of solar and wind power plants is about 33.8 % and 63.5 %, respectively. Approximately 82.6 % of active companies in the renewable energy sector are in the field of solar energy. This information shows that solar and wind energies have attracted the attention of government and digital services companies. Therefore, other renewable energies, such as biomass, hydropower, and WHR, have

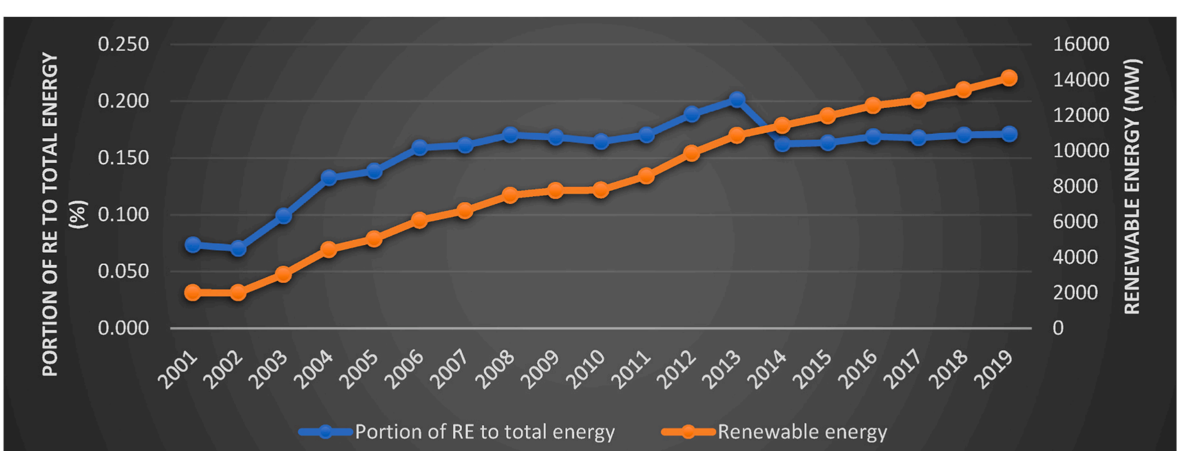

Fig. 6. Renewable energy generation in Iran from 2001 to 2019.

Table 3
Criteria and sub-criteria related to evaluating investment opportunities in REDPs.

Criteria	Sub-criteria	modality	Description	Ref.
Economic	Investment cost	Cost	Equipment installation cost	[26,28,88,89]
	O&M cost	Cost	Labor resource cost, operational budget, and maintenance costs	[26,27,30,89–91]
	Production cost	Cost	Energy conversion cost	[28,34,92]
	Investment payback period	Benefit	The period when the initial capital can be received	[29,93–95]
Technical	Efficiency	Benefit	The rate of output to input	[30,31,96–99]
	Production Capacity	Benefit	Maximum annual energy production rate	[31,91,99,100]
	Technical development	Benefit	Technology reliability and its development at the national level	[26,28,31,89]
Managerial	Political and financial support	Benefit	Government support programs like financial incentives	[32,95,101]
	Compatibility with the National Energy Political Plan	Benefit	Government action plans to promote renewable energies	[32,101–103]
Environmental	GHG emissions	Cost	CO_2 production during the power plan life cycle	[26,27,89,91]
	Land use	Cost	Lands needed to establish power plants	[27,34,88]
Social	Job creation	Benefit	Number of fixed and variable jobs that are created by establishing power plants	[31,88,99,100]
	Social acceptance	Benefit	Social acceptance of renewable energy development in the country	[26,30,90,91]

not developed like solar or wind energies, and the digital services companies have not invested in these REDPs. To solve this problem, the government intends to prioritize investment opportunities based on some criteria related to investment management and renewable energy development and allocate GFI to REDPs. For this purpose, five types of renewable energies, including solar, wind, biomass, hydropower, and WHR, which have the most applications in Iran, are investigated from a sustainable investment perspective. The criteria and sub-criteria used in this paper are presented in Table 3.

Based on Table 3 and the available data on the Renewable Energy and Energy Efficiency Organization in Iran (SABTA) website, the numerical results obtained from evaluating investment opportunities in renewable energy in Iran can be examined using the proposed approaches. Notably, the opinions of some experts employed in some active companies in the renewable energy organization in Iran have been considered to complete the required information [104].

5. Computational results

This section investigates the weighting of the related criteria and sub-criteria and prioritizes REDPs to evaluate investment opportunities in renewable energies in Iran. Moreover, performance validation of the proposed bi-level optimization model is examined. Finally, some managerial insights are presented through sensitivity analysis results. This study implements BWM, VIKOR, and GRA in GAMS 24.1 and MATLAB R2017b. The heuristic is coded in *Python 3.8.3* and runs on a PC with a 3.2 GHz Intel Core i7-640 M CPU and 16 GB of RAM.

The structure of computational results is presented in two sub-sections. First, calculations of the multicriteria decision model are described in two parts: weighting criteria and sub-criteria by BWM and prioritizing REDPs using VIKOR and GRA. Then, sensitivity analysis of criteria weight is performed to select the best prioritization method. Second, based on the presented prioritization by the best method, the applicability of the bi-level model and performance of the developed heuristic are investigated. Moreover, some managerial insights are driven by performing sensitivity analyses.

5.1. Computational results of the MCDM model

The proposed case study considers five types of REDPs in solar, wind, bio-mass, hydropower, and WHR alternatives. There are 13 sub-criteria in economic, technical, managerial, environmental, and social categories. The pairwise comparisons are determined using the opinions of seven experts in some companies related to SABTA.

5.1.1. Weighting the criteria using BWM

The best and the worst criteria and the related preferences are determined through BWM questionnaires completed by some experts in the field of renewable energies. Table 4 shows the weight of criteria and sub-criteria obtained by BWM.

The political and financial support criterion has the highest global weight (0.184), and land use has the lowest (0.023). Payback period, investment cost, efficiency, and compatibility with national energy political plan with global weights (0.137), (0.133), (0.115), and (0.091) are ranked second to fifth, respectively. A detailed calculation related to BWM is presented in Appendix A.

5.1.2. Prioritizing the alternatives using VIKOR and GRA

According to the proposed procedure, the alternatives are evaluated using the experts' views using the linguistic scales 1 to 5 that present the low to the high importance, respectively. After that, an average of the obtained rates is determined. Based on the results presented in Online Resources and the final results in Table 5, solar, wind, and hydropower are ranked as the first, the second, and the third alternatives in both prioritization methods. About the other REDPs, VIKOR ranked WHR as the fourth alternative and biomass as the fifth one. On the contrary, biomass and WHR are reported as the fourth and fifth ones using GRA, respectively.

The numerical distance (ND) between alternative scores obtained by VIKOR and GRA is an applicable measure for comparing the robustness of the proposed methods that is calculated by Equation (25). This measure shows the ranking reliability for each method. Therefore, larger values of this measure indicate higher robustness.

$$ND_{ij} = \frac{|w_i - w_j|}{\sum_i w_i} \quad \forall i \neq j \in \textit{criteria set} \tag{25}$$

According to Table 6, VIKOR reports larger values for ND than GRA in all REDPs pairwise comparisons. For instance, ND for solar and WHR pairwise comparisons are 0.44 by VIKOR and 0.08 by GRA. Hence, VIKOR results in more robustness than GRA in the case study.

5.1.3. Sensitivity analysis for ranking methods

In this sub-section, sensitivity analysis of VIKOR and GRA is performed to evaluate their robustness over changing criteria weights because these changes significantly affect alternative prioritization. For this purpose, two robustness measures R_1 and R_2 are defined. Measure R_1 is related to calculating the number of changes in alternatives'

Table 4
The obtained weights of criteria/sub-criteria.

Criteria	Criteria Weights	Sub-Criteria	Code	Sub-Criteria Weights	Global Weights	Ranking
Economic	0/340	Investment cost	C1	0/391	0/133	3
		O&M cost	C2	0/135	0/046	8
		Production cost	C3	0/069	0/024	12
		payback period	C4	0/404	0/137	2
Technical	0/224	Efficiency	C5	0/513	0/115	4
		Production Capacity	C6	0/200	0/045	9
		Technical development	C7	0/286	0/064	6
Managerial	0/275	Policy & financial support	C8	0/670	0/184	1
		Compatibility with the National Energy Policy Plan	C9	0/330	0/091	5
Environmental	0/052	GHG emissions	C10	0/554	0/029	11
		Land use	C11	0/446	0/023	13
Social	0/085	Job creation	C12	0/563	0/048	7
		Social acceptance	C13	0/437	0/037	10

Table 5
Final prioritization of REDPs using VIKOR and GRA.

Rank	VIKOR		GAR	
	Q	Renewable Energy	Γ	Renewable Energy
1	0	Solar	0.736	Solar
2	0.263	Wind	0.650	Wind
3	0.382	Hydropower	0.633	Hydropower
4	0.624	Biomass	0.513	Waste heat recovery
5	0.996	Waste heat recovery	0.492	Biomass

position concerning the initial ranking. For example, if the alternative initial ranking is $1 > 2 > 3 > 4 > 5$ and after changing the weight of one criterion, the new ranking becomes $4 > 2 > 3 > 1 > 5$, then the measure R_1 will equal one because one change (the rank of alternatives 1 and 4) is applied. In measure R_2, the number and position change weight are taken into account. In the above example, R_2 equals 3 since alternative 1 (or similarly alternative 4) is changed three ranks. For the sensitivity analysis, the weight is set with a 5 % or 50 % increase or decrease of the criterion weight. Figs. 7 and 8 show a comparison of the sensitivity analysis based on R_1 and R_1. To set the criteria weight equal to 1, the remaining criteria must be proportionally decreased when a criterion weight increases.

Fig. 7 shows that based on the measure R_1, changing weights of C3 and C11 does not result in REDP ranking change. These results approve Table 5, which shows that the mentioned criteria have low effects on prioritizing alternatives. Changing weights of C1, C8, and C9 affects REDP prioritization obtained by GRA. The change in weight of C4, C5, and C7 permutes the alternative ranking obtained by GRA. Fig. 8 illustrates that VIKOR and GRA have similar performance over changing weights of C4 and C8. However, changing weights of C5, C6, and C9 significantly affect REDP prioritization obtained by GRA.

As a result, GRA has more significant sensitivity over changing criteria weights than VIKOR. Therefore, VIKOR is selected as the best method for REDP prioritization in the case study because of the robustness of analytical insight.

Table 6
ND measure for VIKOR and GRA.

Energy	Solar		Wind		Hydropower		Biomass		Waste heat recovery	
	VIKOR	GRA	VIKOR	GRA	VIKOR	GRA	VIKOR	GRA	VIKOR	GRA
Solar	–	–	0.12	0.03	0.17	0.03	0.28	0.07	0.44	0.08
Wind	0.12	0.03	–	–	0.05	0.01	0.28	0.07	0.44	0.08
Hydropower	0.17	0.03	0.05	0.01	–	–	0.11	0.04	0.27	0.05
Biomass	0.28	0.07	0.28	0.07	0.11	0.04	–	–	0.16	0.01
WHR	0.44	0.08	0.44	0.08	0.27	0.05	0.16	0.01	–	–

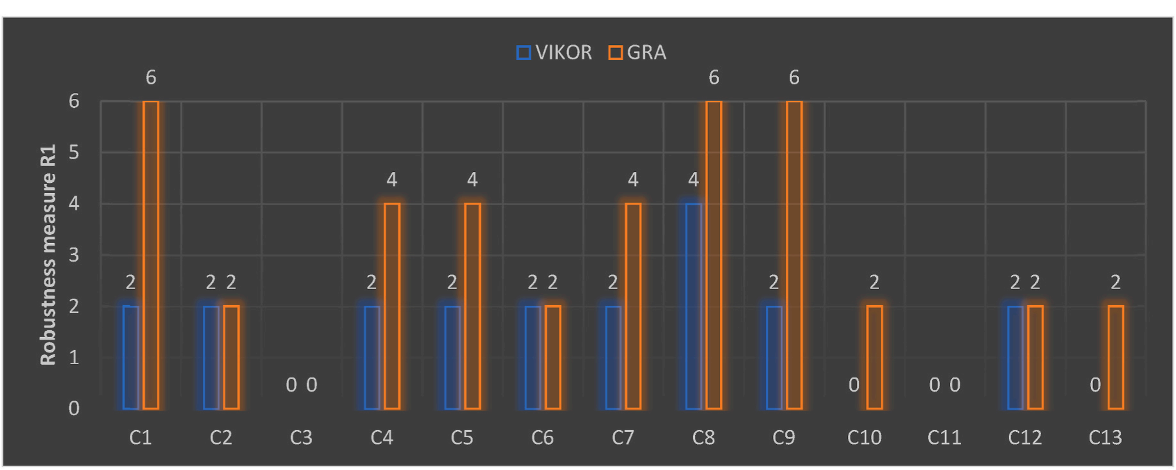

Fig. 7. Robustness analysis of ranking methods using R1.

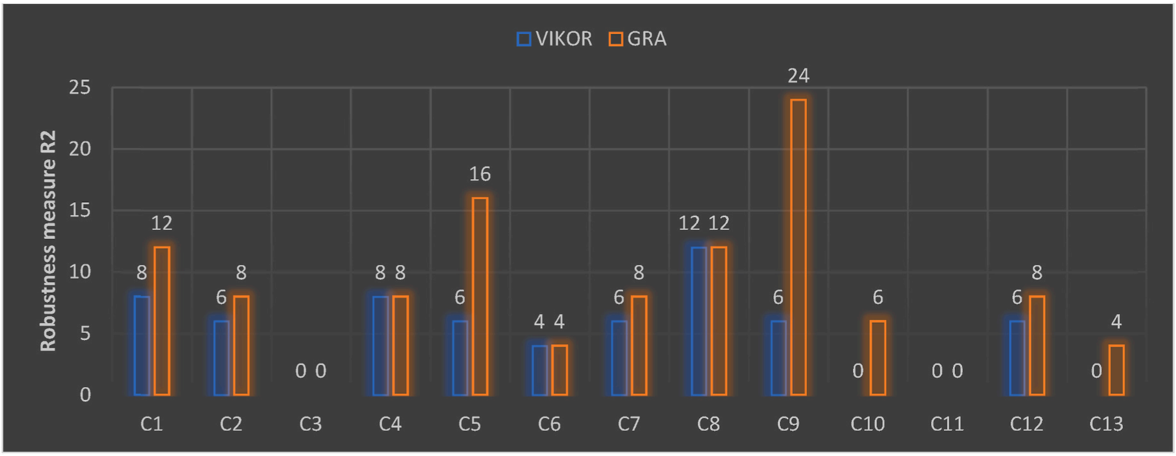

Fig. 8. Robustness analysis of ranking methods using R2.

$$LSS = \left\{ \begin{array}{l} (1),(2),(3),(4),(5),(1,2),(1,3),(1,4),(1,5),(2,3),(2,4),(2,5),(3,4),(3,5),(4,5),(1,2,3),(1,2,4),(1,2,5),(1,3,4), \\ (1,3,5),(1,4,5),(2,3,4),(2,3,5),(2,4,5),(3,4,5),(1,2,3,4),(1,2,3,5),(1,2,4,5),(1,3,4,5),(2,3,4,5),(1,2,3,4,5) \end{array} \right\}$$

5.2. Computational results of the optimization model

In this sub-section, the bi-level model is solved by the proposed heuristic and optimal combination of allocated GFI to the ranked REDPs and the optimal investment amount by digital services companies in each REDP. Before presenting the obtained results, the data collection procedure is explained.

5.2.1. Data collection

The government plans to increase the private sector's investment in less developed renewable energies in Iran. The required data to solve the optimization model is presented in this sub-section. The development preference of each renewable energy project is one of the most critical input parameters calculated by Equation (26).

$$P_i = \sum_{j \in \{Q_j > Q_i\}} ND_{ij} \quad \forall i \in criteria\ set \tag{26}$$

where, Q_i is the rank of ith REDP. In this way, a REDP with a lower rank resulting from VIKOR has a higher priority in persuading digital services companies to invest. L_i and U_i are determined by the decision-maker. Moreover, the total budget for REDPs is assumed to be about \$1100 for 5 KW. Moreover, the annual income for each 5 KW in 2019 is about \$1540, and the initial investment cost is nearly \$2475. It should be noted that the investment cost is considered a fixed cost and is paid for three to five years. F_i and K_i are determined by the digital services companies' preferences. The investment risk for solar, wind, hydropower, biomass, and WHR energies is assumed to be about 8.1 %, 11.7 %, 19.4 %, 24.8 %, and 35.1 %, respectively.

5.2.2. The heuristic performance evaluation

As mentioned in the heuristic framework, all government strategies for REDP selection should be generated to create the *GSS* set. There are five REDPs, including solar (1), wind (2), hydropower (3), bio-mass (4), and WHR (5), in Iran, so all of the feasible combinations of REDPs selection for a government are generated as follow.

$$|LSS| = \binom{5}{1} + \binom{5}{2} + \binom{5}{3} + \binom{5}{4} + \binom{5}{5} = 5 + 2 \times \frac{5!}{2!} + 5 + 1 = 31$$

In the next heuristic step, all optimal combinations of GFI allocation are generated using the proposed local search algorithm presented in Table 7.

The optimal amount of digital services companies' investment in REDPs is determined by optimally solving the private sector company model using the heuristic operators. Thus, creating a feasible decision space for the government to obtain the final solution by the government's objective function is possible. Table 8 shows the numerical results of GFI allocation to different REDP combinations.

The generated variables in Table 7 for each GSS member are inserted into the government model to obtain the final solution. The best combination is the final solution to the problem based on the government's objective function. Therefore, the final solution obtained is a high-quality, near-optimal solution. Fig. 9 illustrates the government's objective function values for each generated x_i and y_i of GSS members.

Fig. 9 shows the optimal values of the government objective function according to the different values of w_i and GSS members. It can be shown that if $N = 1$, LSS_1 is selected as the optimal combination and resulted in 2.265 for the government's objective function, which is the highest value. Only WHR is selected in this combination, and all available budget is allocated. If $N = 5$, the government objective function is equal to 1.01163, which shows the government's desirability decreases for increasing N. For large values of N, the investment of digital services companies is allocated to REDPs that do not have high priority for the government. However, digital services companies tend to invest in more REDPs to minimize the investment risk. Fig. 10 shows the investment risk for a different combination of REDPs.

The government objective function values and the private sector company risk for a different combination of REDPs, which are presented in Figs. 9 and 10, have a similar trend. The high-priority REDPs the government selects are the high-investment risk projects for the private sector companies. This similarity approves the investigated problem in the case study about the high investment risk for the digital services companies in less developed energies selected by SABTA. However, using the proposed approach, the optimal GFI allocation to the digital services companies leads investors to invest despite the high risk, which is precisely the primary purpose of this research. The optimal amount of private sector investment for dual, triple, quadruple, and quintuple

Table 7
The optimal allocated GFI to REDP combinations.

$LSS_1 \rightarrow y_1 = 7419$ $LSS_2 \rightarrow y_2 = 7419$ $LSS_3 \rightarrow y_3 = 7419$ $LSS_4 \rightarrow y_4 = 7419$ $LSS_5 \rightarrow y_5 = 7419$				
$LSS_6 \rightarrow y_1 = 4770$,	$y_2 = 2649$			
$LSS_7 \rightarrow y_1 = 3810$,	$y_3 = 3609$			
$LSS_8 \rightarrow y_1 = 3916$,	$y_4 = 3503$			
$LSS_9 \rightarrow y_1 = 3598$,	$y_5 = 3821$			
$LSS_{10} \rightarrow y_2 = 3112$,	$y_3 = 4307$			
$LSS_{11} \rightarrow y_2 = 3070$,	$y_4 = 4349$			
$LSS_{12} \rightarrow y_2 = 3710$,	$y_5 = 3709$			
$LSS_{13} \rightarrow y_3 = 4505$,	$y_4 = 2914$			
$LSS_{14} \rightarrow y_3 = 1605$,	$y_5 = 5814$			
$LSS_{15} \rightarrow y_4 = 4205$,	$y_5 = 3214$			
$LSS_{16} \rightarrow y_1 = 2473$,	$y_2 = 3916$,	$y_3 = 1030$		
$LSS_{17} \rightarrow y_1 = 1944$,	$y_2 = 3351$,	$y_4 = 2124$		
$LSS_{18} \rightarrow y_1 = 1775$,	$y_2 = 4240$,	$y_5 = 1404$		
$LSS_{19} \rightarrow y_1 = 2164$,	$y_3 = 3928$,	$y_4 = 1327$		
$LSS_{20} \rightarrow y_1 = 1767$,	$y_3 = 3014$,	$y_5 = 2638$		
$LSS_{21} \rightarrow y_1 = 2120$,	$y_4 = 4205$,	$y_5 = 1094$		
$LSS_{22} \rightarrow y_2 = 2192$,	$y_3 = 3351$,	$y_4 = 1876$		
$LSS_{23} \rightarrow y_2 = 1090$,	$y_3 = 2089$,	$y_5 = 4240$		
$LSS_{24} \rightarrow y_2 = 2336$,	$y_4 = 4011$,	$y_5 = 1072$		
$LSS_{25} \rightarrow y_3 = 2164$,	$y_4 = 3928$,	$y_5 = 1327$		
$LSS_{26} \rightarrow y_1 = 861$,	$y_2 = 2758$,	$y_3 = 2222$,	$y_4 = 1578$	$y_5 = 3407$
$LSS_{27} \rightarrow y_1 = 1679$,	$y_2 = 2218$,	$y_3 = 2052$,	$y_5 = 1470$	
$LSS_{28} \rightarrow y_1 = 1324$,	$y_2 = 1489$,	$y_4 = 2272$,	$y_5 = 2334$	
$LSS_{29} \rightarrow y_1 = 617$,	$y_3 = 1078$,	$y_4 = 4592$,	$y_5 = 1232$	
$LSS_{30} \rightarrow y_2 = 2114$,	$y_3 = 353$,	$y_4 = 977$,	$y_5 = 3975$	
$LSS_{31} \rightarrow y_1 = 333$,	$y_2 = 330$,	$y_3 = 1439$,	$y_4 = 1910$,	

Table 8
The amount of digital services companies investment in different combinations of REDPs.

$LSS_1 \rightarrow x_1 = 1$ $LSS_2 \rightarrow x_2 = 1$ $LSS_3 \rightarrow x_3 = 1$ $LSS_4 \rightarrow x_4 = 1$ $LSS_5 \rightarrow x_5 = 1$				
$LSS_6 \rightarrow x_1 = 0.27$,	$x_2 = 0.73$			
$LSS_7 \rightarrow x_1 = 0.57$,	$x_3 = 0.43$			
$LSS_8 \rightarrow x_1 = 0.6$,	$x_4 = 0.4$			
$LSS_9 \rightarrow x_1 = 0.5$,	$x_5 = 0.5$			
$LSS_{10} \rightarrow x_2 = 0.55$,	$x_3 = 0.45$			
$LSS_{11} \rightarrow x_2 = 0.61$,	$x_4 = 0.39$			
$LSS_{12} \rightarrow x_2 = 0.51$,	$x_5 = 0.49$			
$LSS_{13} \rightarrow x_3 = 0.55$,	$x_4 = 0.45$			
$LSS_{14} \rightarrow x_3 = 0.19$,	$x_5 = 0.81$			
$LSS_{15} \rightarrow x_4 = 0.37$,	$x_5 = 0.63$			
$LSS_{16} \rightarrow x_1 = 0.49$,	$x_2 = 0.15$,	$x_3 = 0.35$		
$LSS_{17} \rightarrow x_1 = 0.26$,	$x_2 = 0.16$,	$x_4 = 0.58$		
$LSS_{18} \rightarrow x_1 = 0.38$,	$x_2 = 0.35$,	$x_5 = 0.27$		
$LSS_{19} \rightarrow x_1 = 0.2$,	$x_3 = 0.22$,	$x_4 = 0.58$		
$LSS_{20} \rightarrow x_1 = 0.15$,	$x_3 = 0.27$,	$x_5 = 0.58$		
$LSS_{21} \rightarrow x_1 = 0.36$,	$x_4 = 0.3$,	$x_5 = 0.34$		
$LSS_{22} \rightarrow x_2 = 0.36$,	$x_3 = 0.33$,	$x_4 = 0.32$		
$LSS_{23} \rightarrow x_2 = 0.11$,	$x_3 = 0.3$,	$x_5 = 0.59$		
$LSS_{24} \rightarrow x_2 = 0.41$,	$x_4 = 0.45$,	$x_5 = 0.14$		
$LSS_{25} \rightarrow x_3 = 0.23$,	$x_4 = 0.61$,	$x_5 = 0.16$		
$LSS_{26} \rightarrow x_1 = 0.28$,	$x_2 = 0.09$,	$x_3 = 0.24$,	$x_4 = 0.39$	$x_5 = 0.38$
$LSS_{27} \rightarrow x_1 = 0.15$,	$x_2 = 0.13$,	$x_3 = 0.49$,	$x_5 = 0.23$	
$LSS_{28} \rightarrow x_1 = 0.29$,	$x_2 = 0.46$,	$x_4 = 0.08$,	$x_5 = 0.17$	
$LSS_{29} \rightarrow x_1 = 0.16$,	$x_3 = 0.22$,	$x_4 = 0.38$,	$x_5 = 0.24$	
$LSS_{30} \rightarrow x_2 = 0.43$,	$x_3 = 0.36$,	$x_4 = 0.16$,	$x_5 = 0.06$	
$LSS_{31} \rightarrow x_1 = 0.31$,	$x_2 = 0.21$,	$x_3 = 0.05$,	$x_4 = 0.05$,	

component combinations is illustrated in Fig. 11.

Fig. 11 shows that hydropower and WHR are selected for investment by the digital services companies for $N = 2$. Since WHR has more investment risk than hydropower, the government allocates $1605 as GFI to hydropower and $5814 to WHR for each 5 KW. In other words, digital services companies are encouraged to invest 81 % in WHR and 19 % in hydropower. For $N = 3$, the digital services companies invest 59 % in WHR, 30 % in hydropower, and 11 % in wind energy. The allocated GFI to them is $4020, $2089, and $1090 for each 5 KW, respectively. For $N = 4$, about 38 % of the digital services company's budget is invested in bio-mass energy because the government allocated $4592 for each 5 KW. WHR, hydropower, and solar energies with GFIs equal to $1232, $1078, and $617 are the other projects for the digital services companies with 24 %, 22 %, and 16 % of the total budget. Finally, for $N = 5$, GFI could not completely cover the investment risk effect, and about 52 % of the total investment of digital services companies is allocated to solar and wind energies, known as developed renewable energies in Iran. However, WHR is the main investment project with 38 % of total investment because the government allocated about $3407 for each 5 KW to this type of energy. There is a 5 % digital services companies' investment in biomass and hydropower. However, in the current situation, these types of renewable energies do not have any portion of the investments of digital services companies. As a result, it can be stated that the proposed model and the heuristic significantly improve the GFI allocation to REDPs to persuade digital services companies to invest in high-risk REDPs.

6. Managerial implications

According to the field interviews with some investors in the digital services companies, timely payment of financial resources by the government, government support for importing technical equipment from

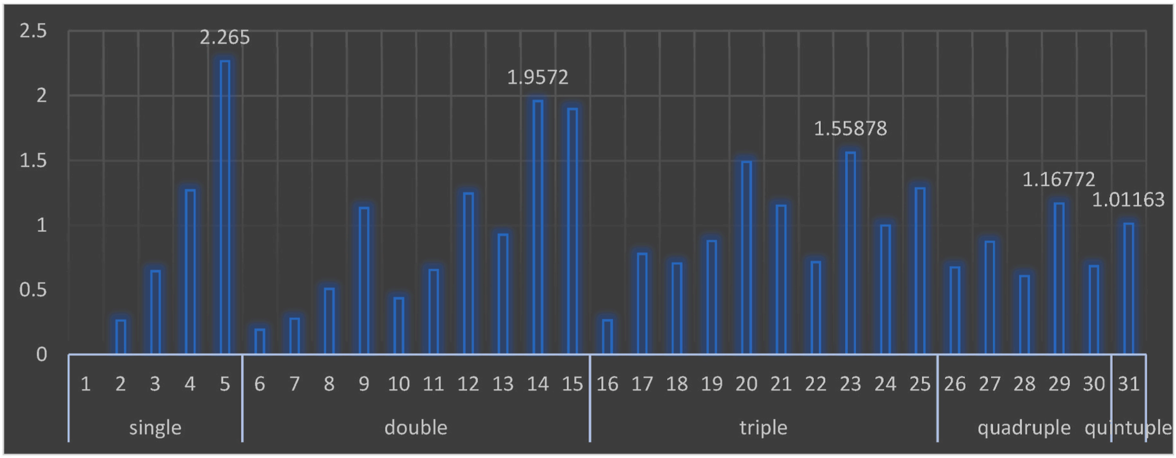

Fig. 9. The government's objective function for different combinations of REDPs.

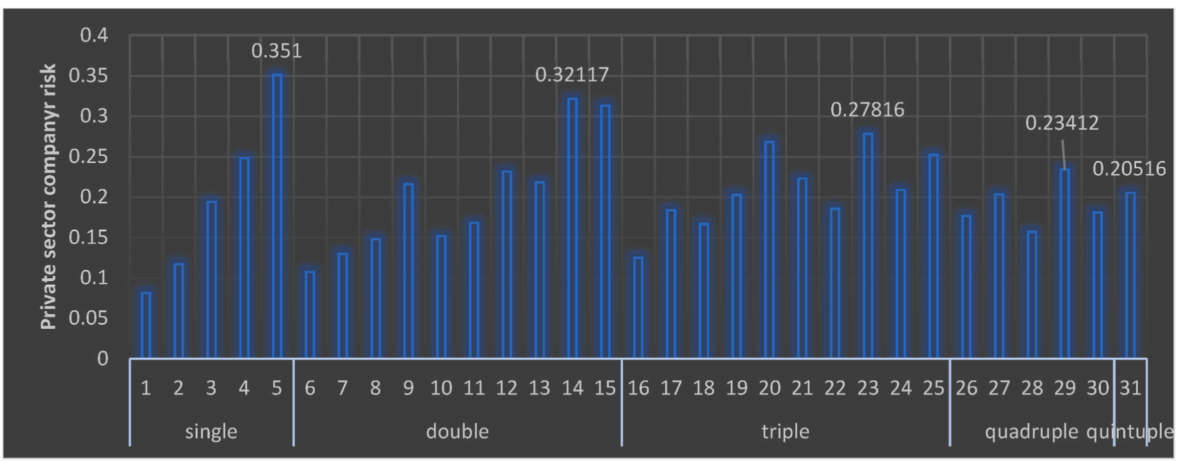

Fig. 10. The private sector company investment risk for different combinations of REDPs.

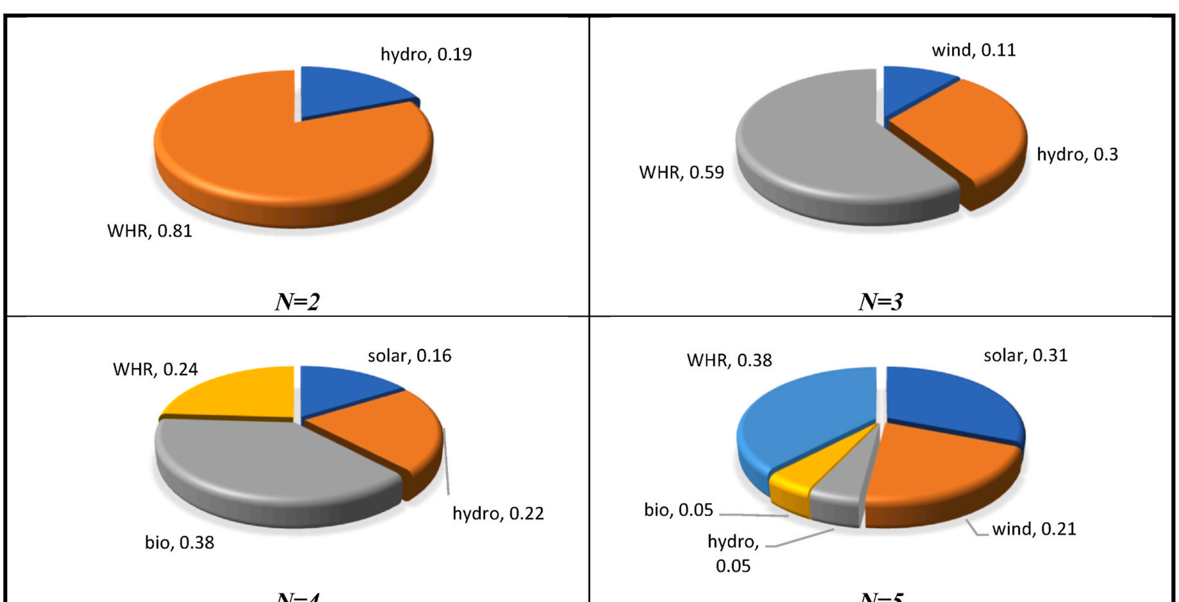

Fig. 11. The optimal values of digital services companies' investment in REDPs.

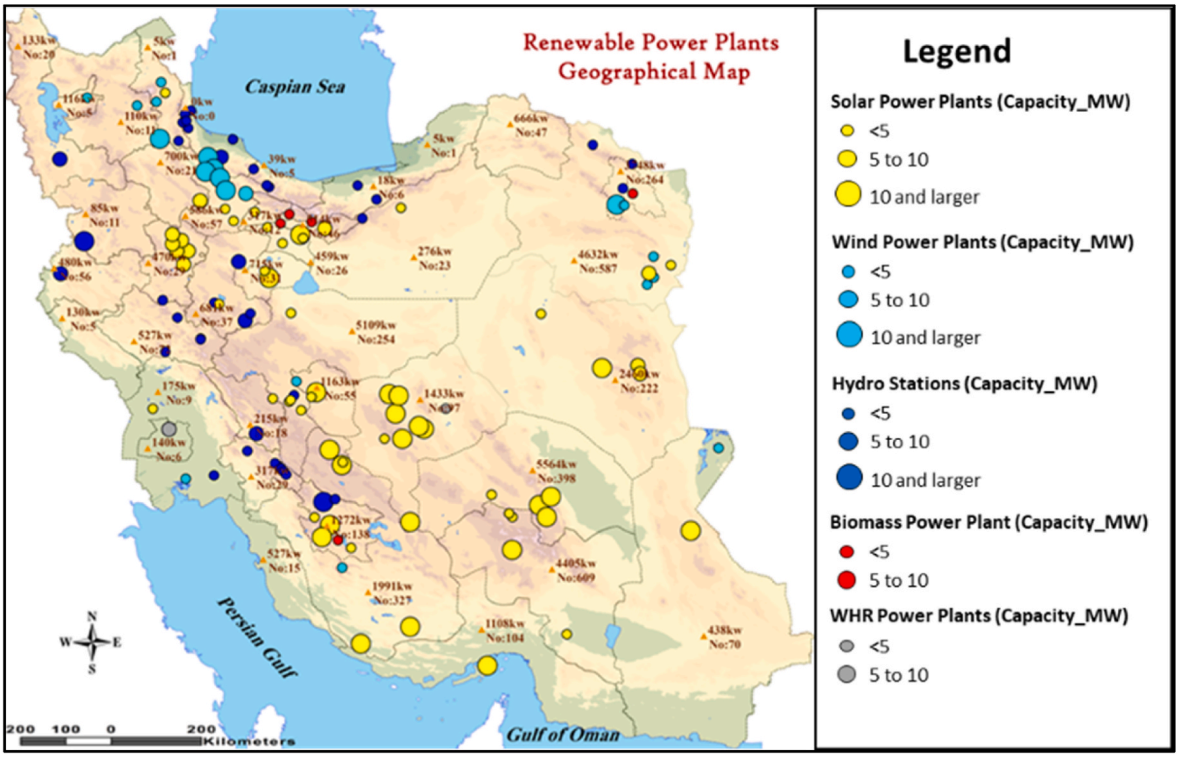

Fig. 12. Geographical distribution of renewable energy powerplants in Iran (http://www.satba.gov.ir/en/home).

some high-tech countries, and fair allocation of low-interest loans are the most critical concerns of the digital services companies to invest in REDPs. Moreover, ensuring initial capital return and minimizing fixed/operational costs are other concerns that digital services companies tend to reduce by making optimal plans. The proposed MCDM model confirms the above problems and shows that political and financial support, payback period, and investment cost significantly affect investment opportunities in REDPs. Since solar and wind energies are the most developed REDPs in Iran (Fig. 12), the government tends to develop other renewable energies, including biomass, hydropower, and WHR, with the help of digital services companies. For this purpose, some GFI is considered to persuade digital services companies to invest in high-risk REDPs.

Based on the optimization model results, WHR and hydropower have the highest allocated GFI because of their high-risk investment value. For N = 4 and N = 5, bio-mass is considered a high-efficiency investment project for digital services companies. The government allocates significant GFI to WHR and hydropower for their development through cooperation with digital services companies.

7. Conclusion and policy implication

This study is a new attempt to develop a novel approach for evaluating investment opportunities in REDPs and GFI optimal allocation in Iran. This hybrid approach is proposed based on MCDM methods and a bi-level optimization model that can be useful in deciding on a renewable energy system. The proposed MCDM model is designed based on BWM to weigh the related criteria and VIKOR and GRA to prioritize REDPs as alternatives. The optimization model is developed based on bi-level mathematical modeling where the government and the private sector companies are competitive. Since bi-level models are strongly NP-hard problems, this paper developed a new iterative full-enumeration-based heuristic based on a classical non-cooperative Stackelberg game. The extended heuristic finds the final solution by replacing the optimal solutions of private sector companies calculated according to the generated feasible government strategies with the government model and extracting the best one based on the government objective function. This procedure results in a near-optimal solution based on the Stackelberg equivalent conception. Computational results illustrate that "political and financial support" and "land use" are the most and the least important criteria, respectively.

Moreover, considering the government plans to increase the investment of digital services companies in less developed renewable energies, WHR and hydropower energies are preferred. At the same time, private sector companies tend to invest in solar and wind energies as low-risk projects. The heuristic results show that hydropower and WHR are selected for investment by the digital services companies for $N = 2$. Since WHR has more investment risk than hydropower, the government allocates \$1605 as GFI to hydropower and \$5814 to WHR for each 5 KW. Therefore, digital services companies are encouraged to invest 81 % in WHR and 19 % in hydropower. For $N = 3$, the digital services companies invested 59 % in WHR, 30 % in hydropower, and 11 % in wind energy because the allocated GFI are \$4020, \$2089, and \$1090 for each 5 KW. For $N = 4$, about 38 % of the digital services company's budget is invested in bio-mass energy because the government allocated \$4592 for each 5 KW. WHR, hydropower, and solar energies with GFI equal to \$1232, \$1078, and \$617 are the other investable projects for the digital services companies with 24 %, 22 %, and 16 % of the total budget. Finally, for $N = 5$, GFI could not completely cover the investment risk effect. About 52 % of the total private sector investment is allocated to solar and wind energies, known as the developed renewable energies in Iran. However, WHR is the leading investment project with 38 % of total investment because the government allocates about \$3407 for each 5 KW to this type of REDP. For biomass and hydropower, there is a 5 % investment from the digital services companies; however, in the current situation, these types of renewable energies do not have any portion of private sector investment. Hence, SABTA experts believe that a managerial problem is finding an efficient GFI payment policy under government supervision. According to the SABTA experts, the main problem is finding an efficient policy to pay GFI under government supervision. This paper suggests four policies in Table 9 to achieve the best performance in REDPs.

Table 9
Suggested policies for GFI payment to REDPs.

Policy	Description	Suggestion for implementation
Direct Cash Incentives	These incentives take different forms, like performance-based incentives, rebates, buydowns, and grants. Rebates are issued as payments to the system installer after the installation is complete. A buydown is a reduction in the bottom-line cost of the system for the buyer. Grants, generally used for large projects, are more complex and have a competitive application process. These incentives are based on system capacity, percentage of capital cost, or expected system performance. However, performance-based incentives are based on the output energy of the system and are disbursed over several years.	✓These incentives should be provided until the industry can compete with the coal and oil-based energy industries in terms of cost and market capacity. ✓Policymakers in this field should meet solely to discuss and modify the various bottlenecks to support the industry most efficiently.
Property Tax Incentives	This incentive mitigates or eliminates rising property value from installing renewable energy systems. Since renewable energy systems are associated with high installation costs, they result in the elevated value of the property. This could be a hindrance to renewable energy systems in the future. Property tax incentives significantly encourage installing renewable energy systems on a property.	✓Provide explicit property tax exemption for installed renewable energy systems rather than providing credit since providing credits can benefit some and not others.
Sales Tax Incentives	This incentive provides an exemption from sales tax on the purchase and installation of renewable energy systems to help reduce a certain portion of the high cost incurred during its purchase and installation. Sales tax varies from state to state, resulting in varied incentives from state to state.	✓This incentive is vital in highlighting the significance of renewable energy systems by providing buyers with tax incentives and making them feel it is essential to achieving energy independence.
Loan Programs	These programs encourage the installation of renewable energy systems by addressing the financial barrier of high installation costs. Though they do not reduce the cost, they help reduce it over some time.	✓More states should develop fund-generating methods like those mentioned in the example so that these loan programs do not affect the state budget. ✓More accountability in case a person or company shifts from one property to another or associates the system with the property.

These policies can guarantee the success of the GFI allocation plan for developing renewable energies in Iran, and the digital services companies can also use government financial resources appropriately.

It should be noted that the current study has some limitations in theory and practice, which are discussed below. First, in response to recognizing the diverse nature of GFIs and their potential impact on project return and risk, this paper acknowledges the need for a more nuanced treatment of GFIs in the optimization model. The assumption in this paper that different types of GFIs can be converted to a cash form, as reflected in the inclusion of the variable y_i in equation (8) representing the rate of return for the private investor, is acknowledged. Future research can explicitly account for the distinct characteristics of various GFI forms that address this. GFIs will be categorized into direct and indirect financial support programs, aligning with classifications available in the Private Participation in Infrastructure database from the World Bank. The aim could be to provide a more comprehensive understanding of how different GFI types influence private-sector investment dynamics in renewable energy projects.

Furthermore, this future agenda can commit to delving into the implications of indirect support programs, exploring how guarantees related to payment, debt, revenue, exchange rate, construction cost, and interest rate may impact the risk faced by private investors in PPPs. These enhancements aim to accurately represent the diverse forms of GFIs and their effects on private sector investment in renewable energy projects. This refinement considers the intricate aspects of GFIs. It is crucial to the model's robustness, striving to capture their diverse forms and their effects on private sector investment dynamics in renewable energy projects.

Second, the bi-level optimization model encompasses the nuanced consideration of risk by incorporating the rate of return for the private investor. This rate of return, shaped by the allocation of GFIs, encapsulates the investor's perception of risk. The iterative full-enumeration-based heuristic further refine the understanding of how private investors, each with unique risk appetites, strategically approach their investment decisions within the PPP framework. To enhance clarity, as a future research agenda, a deeper exploration can be undertaken into how the specific contractual forms of PPPs influence risk allocation. This expansion should comprehensively explore the risk-return dynamics inherent in the PPP context, ensuring a nuanced understanding of how risks are distributed between public and private partners.

As another suggestion for developing the proposed problem in this paper, considering the input parameters under interval uncertainty and developing a robust approach can be applied to future research. Moreover, one can extend this work by developing models and solution algorithms for problems that integrate the capacity expansion of energy services and investment decisions. Moreover, potential future research may investigate variations in conditions set by private partners, assess the influence of diverse selection methods, and analyze the resultant implications for the proposed optimization model. Through delving into these aspects, a more comprehensive understanding of the multifaceted considerations inherent in PPPs can be achieved, thereby making a substantive contribution to the progress of the research field.

CRediT authorship contribution statement

Sobhan Mostafayi Darmian: Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Madjid Tavana:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis. **Samuel Ribeiro-Navarrete:** Writing – review & editing, Writing – original draft, Visualization, Validation, Investigation.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.seps.2024.101953.

Appendix A. calculation of BWM in detail

Table A.1
Pairwise comparisons for main criteria by experts (Best-to-other)

Expert	Best criteria	Economic	Technical	Managerial	Environmental	Social
1	Economic	1	3	2	9	7
2	Economic	1	2	2	8	5
3	Managerial	3	2	1	7	6
4	Technical	3	1	3	8	4
5	Economic	1	3	3	8	4
6	Managerial	2	3	1	9	6
7	Economic	1	3	4	9	6

Table A.2
Pairwise comparisons for main criteria by experts (Other-to-worst)

Worst criteria	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Expert 7
	Environmental	Social	Environmental	Environmental	Social	Environmental	Environmental
Economic	9	7	5	4	8	6	9
Technical	6	7	6	9	7	7	5
Managerial	5	6	8	5	6	9	6
Environmental	1	3	1	1	3	1	1
Social	3	1	3	2	1	3	2

Table A.3
Local optimal weights of main criteria

Main Criteria	DMs							Average local weights
	1	2	3	4	5	6	7	
Economic	0.448	0.383	0.172	0.177	0.437	0.263	0.500	**0.340**
Technical	0.174	0.251	0.258	0.463	0.212	0.176	0.203	**0.248**
Managerial	0.261	0.251	0.434	0.177	0.212	0.435	0.152	**0.275**
Environmental	0.041	0.063	0.051	0.049	0.08	0.038	0.043	**0.052**
Social	0.075	0.053	0.086	0.133	0.059	0.088	0.101	**0.085**
ξ	0.035	0.041	0.098	0.081	0.041	0.023	0.028	**0.050**

Table A.4
Pairwise comparisons for economic sub-criteria by experts (Best-to-other)

Expert	Best criteria	Investment cost	O&M cost	Production cost	payback period
1	Investment cost	1	5	7	3
2	payback period	2	3	8	1
3	O&M cost	2	1	6	3
4	Investment cost	1	7	4	4
5	payback period	2	5	8	1
6	Investment cost	1	4	9	5
7	payback period	2	3	7	1

Table A.5
Pairwise comparisons for economic sub-criteria by experts (Other-to-worst)

Worst criteria	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Expert 7
	Production cost	Production cost	Production cost	O&M cost	Production cost	Production cost	Production cost
Investment cost	7	5	7	9	7	9	7
O&M cost	5	6	9	1	7	8	6
Production cost	1	1	1	3	1	1	1
payback period	5	7	8	6	9	7	9

Table A.6
Local optimal weights of economic sub-criteria

Economic	Experts							Average local weights
	1	2	3	4	5	6	7	
Investment cost	0.561	0.286	0.156	0.573	0.329	0.545	0.289	**0.391**
O&M cost	0.142	0.190	0.052	0.058	0.132	0.177	0.193	**0.135**
Production cost	0.059	0.048	0.059	0.184	0.042	0.042	0.051	**0.069**
payback period	0.237	0.476	0.733	0.184	0.497	0.236	0.467	**0.404**
ξ	0.062	0.023	0.042	0.017	0.027	0.076	0.021	**0.038**

Table A.7
Pairwise comparisons for technical sub-criteria by experts (Best-to-other)

Expert	Best criteria	Efficiency	Production Capacity	Technical development
1	Efficiency	1	8	5
2	Technical development	3	9	1
3	Technical development	2	9	1
4	Efficiency	1	8	3
5	Production Capacity	3	1	7
6	Efficiency	1	8	7
7	Efficiency	1	3	8

Table A.8
Pairwise comparisons for technical sub-criteria by experts (Other-to-worst)

Worst criteria	Expert 1 Production Capacity	Expert 2 Production Capacity	Expert 3 Production Capacity	Expert 4 Production Capacity	Expert 5 Technical development	Expert 6 Production Capacity	Expert 7 Technical development
Efficiency	7	5	4	8	4	8	9
Production Capacity	1	1	1	1	7	1	5
Technical development	4	8	7	3	1	5	1

Table A.9
Local optimal weights of technical sub-criteria

Technical	Experts							Average local weights
	1	2	3	4	5	6	7	
Efficiency	0.770	0.253	0.304	0.683	0.125	0.786	0.671	**0.513**
Production Capacity	0.130	0.067	0.071	0.083	0.722	0.071	0.257	**0.200**
Technical development	0.100	0.680	0.625	0.233	0.153	0.143	0.071	**0.286**
ξ	0.036	0.016	0.034	0.021	0.015	0.077	0.056	**0.036**

Table A.10
Pairwise comparisons for managerial sub-criteria by experts (Best-to-other)

Expert	Best criteria	Policy & financial support	Compatibility with National Energy Policy Plan
1	Policy & financial support	1	8
2	Policy & financial support	1	8
3	Compatibility with National Energy Policy Plan	8	1
4	Compatibility with National Energy Policy Plan	7	1
5	Policy & financial support	1	9
6	Policy & financial support	1	8
7	Policy & financial support	1	8

Table A.11
Pairwise comparisons for managerial sub-criteria by experts (Other-to-worst)

Worst criteria	Expert 1 Compatibility with National Energy Policy Plan	Expert 2 Compatibility with National Energy Policy Plan	Expert 3 Policy & financial support	Expert 4 Policy & financial support	Expert 5 Compatibility with National Energy Policy Plan	Expert 6 Compatibility with National Energy Policy Plan	Expert 7 Compatibility with National Energy Policy Plan

(*continued on next page*)

Table A.11 (*continued*)

Policy & financial support	8	9	1	1	8	8	7
Compatibility with National Energy Policy Plan	1	1	9	1	1	1	1

Table A.12
Local optimal weights of managerial sub-criteria

Technical	Experts							Average local weights
	1	2	3	4	5	6	7	
Policy & financial support	0.889	0.889	0.111	0.125	0.900	0.889	0.889	0.670
Compatibility with the National Energy Policy Plan	0.111	0.111	0.889	0.875	0.100	0.111	0.111	0.330
ξ	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table A.13
Pairwise comparisons for environmental sub-criteria by experts (Best-to-other)

Expert	Best criteria	GHG emissions	Land use
1	GHG emissions	1	8
2	Land use	8	1
3	GHG emissions	1	7
4	GHG emissions	1	7
5	GHG emissions	1	8
6	Land use	8	1
7	Land use	7	1

Table A.14
Pairwise comparisons for environmental sub-criteria by experts (Other-to-worst)

Worst criteria	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Expert 7
	Land use	GHG emissions	Land use	Land use	Land use	GHG emissions	GHG emissions
GHG emissions	7	1	8	7	7	1	1
Land use	1	8	1	1	1	8	8

Table A.15
Local optimal weights of environmental sub-criteria

Environmental	Experts							Average local weights
	1	2	3	4	5	6	7	
GHG emissions	0.889	0.111	0.875	0.875	0.889	0.111	0.125	**0.554**
Land use	0.111	0.889	0.125	0.125	0.111	0.889	0.875	**0.446**
ξ	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**0.000**

Table A.16
Pairwise comparisons for social sub-criteria by experts (Best-to-other)

Expert	Best criteria	Job creation	Social acceptance
1	Social acceptance	7	1
2	Job creation	1	9
3	Job creation	1	9
4	Social acceptance	7	1
5	Job creation	1	8
6	Social acceptance	8	1
7	Job creation	1	8

Table A.17
Pairwise comparisons for social sub-criteria by experts (Other-to-worst)

Worst criteria	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Expert 7
	Job creation	Social acceptance	Social acceptance	Job creation	Social acceptance	Job creation	Social acceptance
Job creation	1	8	7	1	7	1	7
Social acceptance	8	1	1	9	1	9	1

Table A.18
Local optimal weights of social sub-criteria

Social	DMs							Average local weights
	1	2	3	4	5	6	7	
Job creation	0.125	0.900	0.900	0.125	0.889	0.111	0.889	**0.563**
Social acceptance	0.875	0.100	0.100	0.875	0.111	0.889	0.111	**0.437**
ξ	0.000	0.000	0.000	0.000	0.000	0.000	0.000	**0.000**

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