Renewable and Sustainable Energy Reviews 208 (2025) 115052

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

Evaluating smart grid investment drivers and creating effective policies via a fuzzy multi-criteria approach

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ARTICLE INFO

Keywords:
Smart grid investment
Renewable energy projects
Weighted DEMATEL
WASPAS
MCDM
Fuzzy sets

ABSTRACT

It is critical to determine which factors impact more smart grid investments and which smart grid investment policy is more suitable for renewable energy projects. Nonetheless, a limited amount of research has focused on this topic, meaning a new study is needed to fill this gap and aid in making decisions under ambiguities. Thus, this research proposes a novel fuzzy group decision-making framework. Twelve drivers are examined through the fuzzy weighted decision-making trial and evaluation laboratory (F–DEMATEL–W) methodology. Subsequently, four smart grid investment policies are ranked using fuzzy weighted aggregated sum product assessment (F–WASPAS). Hence, one of the novelties of this research is the proposal of a robust decision-making tool named F–DEMATEL–W–WASPAS. Other novelties are: (i) the importance of the indicators/criteria is methodically determined by considering pairwise interactions and weights of experts; (ii) both individualistic expert-driven weight vector and cumulative weight vector of indicators are determined; (iii) alternative policies are ranked with minimum decision parameters; (iv) drivers that are crucial for the effectiveness of smart grid investment are determined with their causal relationship, and (v) smart grid investment policies are ranked reliably. The findings demonstrate that cyber security, sufficient legal procedures, and financial viability are the foremost drivers to increase the effectiveness of smart grid investments. Moreover, encouraging sustainable energy production using financial incentives is the foremost policy, followed by exchanging surplus electricity for the system owners. The work may contribute to the ongoing discussion on designing smart grid investment policies for renewable energy projects.

Nomenclature

Abbreviations	
F-DEMATEL-W	Fuzzy weighted decision-making trial and evaluation laboratory
F-WASPAS	Fuzzy weighted aggregated sum product assessment
MCDM	Multi-criteria decision-making
IT	Information technology
B	Bad
ALB	A little bad
VB	Very bad
M	Medium
VG	Very good
G	Good
ALG	A little good
AHP	Analytical hierarchy process
TODIM	Interactive multi-criteria decision-making (in Portuguese)
CODAS	Combinative distance-based assessment
CoCoSo	Combined compromise solution
FST	Fuzzy set theory
Notations	
e	Number of experts
n	Number of criteria
p, q	Any two criteria
k	Index for expert
i	Index for alternative
j	Index for criterion
$u_{pq,k}$	Fuzzy value associated with criterion q and criterion p for an expert k
N	Normalized matrix
T	Relational matrix
I	Identity matrix

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https://doi.org/10.1016/j.rser.2024.115052
Received 25 November 2023; Received in revised form 24 September 2024; Accepted 23 October 2024
Available online 30 October 2024
1364-0321/

(*continued*)

R_p	Row sum value for criterion p
C_q	Column sum value for criterion q
$W_{j,k}$	Weight of criterion j based on the rating from expert k
W_j	Cumulative weight of criterion j
λ_k	Attitude value of expert k
M_i	Weighted sum value for alternative i
D_i	Weighted product value for alternative j
u_{ij}	Fuzzy value for alternative i over criterion j
K_i	Net rank value of alternative i
α	Strategy value

1. Introduction

Smart grids are energy management systems in which modern technology makes energy distribution more effective. This way, it aims to obtain and use electricity more efficiently, sustainably, and cleanly. In this process, smart meters can instantly monitor the amount of energy consumed. Thanks to this control system, it is possible to take measures faster to solve problems in the energy production and consumption process [1]. In other words, energy companies can make the right investment decisions by making more accurate plans. This contributes significantly to increasing the effectiveness and efficiency of the process. Additionally, intelligent grids further support expanding the use of renewable energy and, due to effective energy storage technologies, obtaining uninterrupted electricity from renewable energy sources [2]. Thus, it is possible to minimize the carbon emission problem. Moreover, these networks enable clean energy at lower costs.

Smart systems are essential due to some crucial issues, such as ensuring energy efficiency and increasing the use of clean energy. As such, taking the necessary actions to increase smart grid investments is critical. Financial considerations are of utmost importance to increase the effectiveness of smart grid investments [3]. In this regard, projects should be profitable and sustainable. Otherwise, investors will only turn to these projects if they are environmentally friendly. Achieving customer satisfaction is further necessary for smart grids to work more effectively. This allows businesses to be preferred by more customers. Legal procedures should be sufficient to increase the effectiveness of smart grid investments. This situation gives consumers and investors more confidence in these projects [4]. Additionally, enough technological development is necessary for these network investments to succeed. It is possible to obtain more data with the application of new technology. As predicted, many variables affect the profitability of smart grid projects. So, businesses need to prioritize some improvements due to budget constraints. Otherwise, costs will increase radically. As a result, it is necessary to determine which drivers have the most impact on the effectiveness of smart grid investments. A significant part of the studies has focused on what these drivers are. However, it is necessary to determine which of these drivers is more critical. Additionally, based on the findings, effective policies for renewable energy projects are required. This situation can be accepted as the central gap in the state-of-the-art. Consequently, a new study is needed to bridge these gaps. Using this priority evaluation, it can be possible to identify these projects' most critical performance indicators. This condition helps to implement appropriate investment strategies more efficiently.

Motivated by the discussions, this research aims to evaluate the drivers of smart grid investments and rank the alternative policies for renewable energy projects by constructing a new fuzzy group decision-making model. Twelve different indicators are selected based on the literature review results in this context. These criteria are weighted using the fuzzy weighted decision-making trial and evaluation laboratory (F–DEMATEL–W) methodology with fuzzy information. Subsequently, four alternative policies are ranked with the help of fuzzy aggregated sum product assessment (F–WASPAS). The leading contributions of the study are as follows.

- Fuzzy set theory (FST), a simple and practical concept practitioners could adopt effectively, is utilized to model uncertainty and vagueness.
- Weight values of drivers (criteria) are methodically obtained by taking pairwise criteria interactions and weights of experts into consideration.
- Both individualistic and cumulative weight vectors of drivers are determined.
- It is investigated which drivers determine the effectiveness of smart grid investments the most.
- Alternative policies for renewable energy projects are ranked with minimum decision parameters.
- More efficient investment strategies can be implemented without having too high costs.

Further, novelties of the research are as follows.

- Criteria interactions through cause-effect relationships can be captured by the weight determination approach, considering experts' opinions and attitudinal traits modeled via the weight factor. Therefore, the F–DEMATEL–W methodology is offered for the first time.
- For the first time, the F–DEMATEL–W–WASPAS framework is developed. Combining fuzzy sets with the DEMATEL–W, and WASPAS approach is a novel integration. To the authors' knowledge, it is the first time such an integrated multi-criteria approach has been presented for a smart grid energy scheme selection application.
- Drivers that play a role in the effectiveness of smart grid investments can be prioritized successfully, and alternative policies for renewable energy projects are ranked reliably via the proposed framework.

The following section reviews smart grid investment studies and presents research gaps. Section 3 details the research methodology. The developed DEMATEL–W framework is introduced in this context, and then the F–WASPAS model is presented. Section 4 covers the results of the case study. It also includes sensitivity analysis to display the reliability and practicality of the proposed methodology. Section 5 is reserved for discussion, and the last section concludes the study, including future work and limitations.

2. Studies on smart grid investments

In many studies, it is understood that financial issues are considered in the effectiveness of smart grid investments. Investors need much capital to make these network investments [5]. Rapid access to financial resources is paramount in this process [6]. In this way, making investments becomes much more manageable. Gupta and Shankar [7] determined that for smart grid investments to be completed successfully, possible cash flows must be determined accurately. Accurately estimating the projects' likely revenues and costs is vital.

Ensuring customer satisfaction contributes to the success of smart grid projects in many ways. Satisfied customers are willing to use this system more. As such, businesses that are more preferred by customers can also be more successful [8]. One of the foremost advantages of smart grids is that they offer customers the opportunity to save energy. Investments can be expected to face some financial risks as customers do not want to overpay for electricity use. In this regard, Dorji et al. [9] stated that liquidity risk is vital for these projects. Therefore, smart grids should provide this information to customers entirely and promptly. Hussain et al. [10] determined that another advantage of smart grids is that they provide uninterrupted energy to customers. This allows customers' expectations to be met well. Chandel and Naruka [11] concluded that in order not to lose this advantage, the efficiency of energy storage systems within networks needs to be increased. Bandeiras et al. [12] showed that in this way, businesses can gain a significant competitive advantage by better meeting customer expectations.

Legal procedures should be sufficient to increase the effectiveness of smart grid investments. There are pretty complex processes in smart grid investments [13]. Adequate legal processes contribute to the more effective operation of these projects. In other words, effective legal procedures help investors focus on these projects [14]. Investors who have increased confidence in these processes invest more in these projects. Yao et al. [15] indicated that investors need a legal basis to ensure the long-term sustainability of projects. Beyond that, legal regulations are also critical to safeguard the confidentiality of personal data. Abdulkader et al. [16] state that this condition increases consumer confidence. Another advantage of effective legal processes is that they provide the necessary regulations for competitive conditions in the market. Patel et al. [17] defined this situation as allowing more investors to invest in these projects. The adequacy of legal frameworks also includes comprehensive information about government incentives. This situation helps people access financial resources more efficiently.

Technological development must be sufficient to increase the effectiveness of smart grid investments. These developments enable networks to operate more reliably and efficiently [18]. Smart grids contain information about a large number of users. Therefore, to manage this data correctly, businesses should have the necessary technological infrastructure [19]. Thanks to new technology, it is possible to analyze these data effectively. Mishra and Mishra [20] identified that this situation allows more accurate investment decisions. Advanced technologies further help smart grid investors establish better relationships with customers. Alsolami et al. [21] underlined that customer satisfaction can bring a crucial competitive advantage to businesses. Further, new technology makes working with more successful smart meters possible. According to Sun et al. [22], this helps analyze energy production and consumption data more accurately and comprehensively. Technological developments enable the necessary measures to be taken to protect energy networks against possible cyberattacks more successfully [23].

Some issues are obtained as a result of the literature review. Smart grid systems are projects that are very necessary for energy efficiency. Increasing these projects' effectiveness helps improve the success of energy investments and helps countries achieve energy independence. Therefore, the issues affecting these projects' success need to be improved. Moreover, businesses should prioritize some improvements to prevent their costs from increasing radically due to budget constraints. In this vein, the research questions are as follows.

RQ1. What factors affect smart grid investments?

RQ2. What are the most crucial of these factors?

RQ3. Which smart grid investment policy is more suitable for renewable energy projects?

Though the significance of these drivers has been emphasized, a limited number of studies identify the most critical factors (Table 1). To eliminate this gap in the state-of-the-art, this research aims to determine the paramount drivers and rank policies for renewable energy projects in terms of these drivers by establishing a new fuzzy group decision-making model.

As mentioned earlier, smart grid investment evaluation is a complex decision problem that involves multiple criteria and is an unexplored area in the field of smart energy. Based on the review summary provided on smart grid-related decision-making, certain inferences can be made: (i) FST is a popular mechanism for rating alternatives and decision-making of smart grids; (ii) criteria interactions are not considered during criteria weight calculations; (iii) attitudinal traits of experts are also not considered during criteria weight estimations; and (iv) two or more decision parameters are required for rational ranking of alternatives.

From the review and inferences, it is clear that (i) FST can model uncertainty from only one dimension; therefore, it can be a potential option for rating. The simplicity and practicality of the FST facilitate its usage, and hence, the authors are motivated to utilize FST in this work; (ii) since experts are substantial entities in the decision process, consideration of their attitudinal trait is essential and hence, authors embedded attitudinal traits of experts in criteria weight calculation along with the ability of the method to consider criteria interactions; and (iii) WASPAS method is presented for ranking the alternatives (smart grid investments) with strategy values as the only decision parameter.

Table 1
Research gaps from the extant models pertaining to smart grids.

Sources	Fuzzy set	Criteria interaction	Experts' attitudinal trait	Number of decision parameters in ranking method	Decision parameters in ranking methods
[24]	Picture fuzzy rough	No	No	Two	Criteria type and strategy value
[25]	Fuzzy	No	No	n/a	n/a
[26]	Fuzzy	No	No	Two	Criteria type and strategy value
[27]	Fuzzy	No	No	Two	Consistency check and repair
[28]	Fuzzy	No	No	Two	Consistency check and repair
[29]	Fuzzy	No	No	Two	Consistency check and repair
[30]	Fuzzy	No	No	2	Criteria type and strategy value

Note: n/a is not applicable – as the approach is not a part of multi-criteria decision-making (MCDM) methods.

The model proposed in Section 3 considers these research gaps, and attempts are made to address them. F-DEMATEL-W, along with F-WASPAS, is an integrated approach presented stepwise in the fourth section and is combined to form the decision model that is not only easy for experts to implement but also effective in alleviating the identified research challenges/gaps. As a result, a simple yet effective model has been put forward in this research, which can rationally aid in the decision-making of smart grid investments.

3. Research methodology

This section provides the step-by-step procedure for determining the decision parameters. Specifically, weights of criteria and ranks of investment schemes for energy are chosen to aid in rational decision-making and provide a suitable framework that experts/policymakers can use to support their decisions. Fig. 1 provides the pictorial representation of the developed decision framework. It can be seen from Fig. 1 that there are two phases, where Phase 1 concentrates on data collection and preparation for feeding into the method phase (Phase 2). Experts are tasked with identifying the determinants of smart grid investments, including reviewing several possible alternative policies for renewable energy projects and shortlisting four potential policies based on the voting principle. Later, these policies are rated by twelve diverse drivers as criteria. The experts rate the criteria and policies qualitatively via the Likert scale. These are then transformed into fuzzy sets. After conversion, the data is sent to Phase 2. In the method phase, a pairwise comparison matrix from each expert is fed as input to the procedure in Subsection 3.1. Based on the formulation, a vector of $1 \times n$ is obtained, with n being the number of criteria. Each expert obtains a vector, which is aggregated to get the weights. The weight vector, along with the rating values from each expert for policies, are fed as input to the ranking module that determines the rank values for each potential policy, and finally, a ranking is obtained. A vector of $1 \times m$ is obtained, with m being the number of alternative policies. The procedure for calculating weights and rank values is provided in the following subsections.

More clearly, regarding Fig. 1, the Likert-scale data from experts are

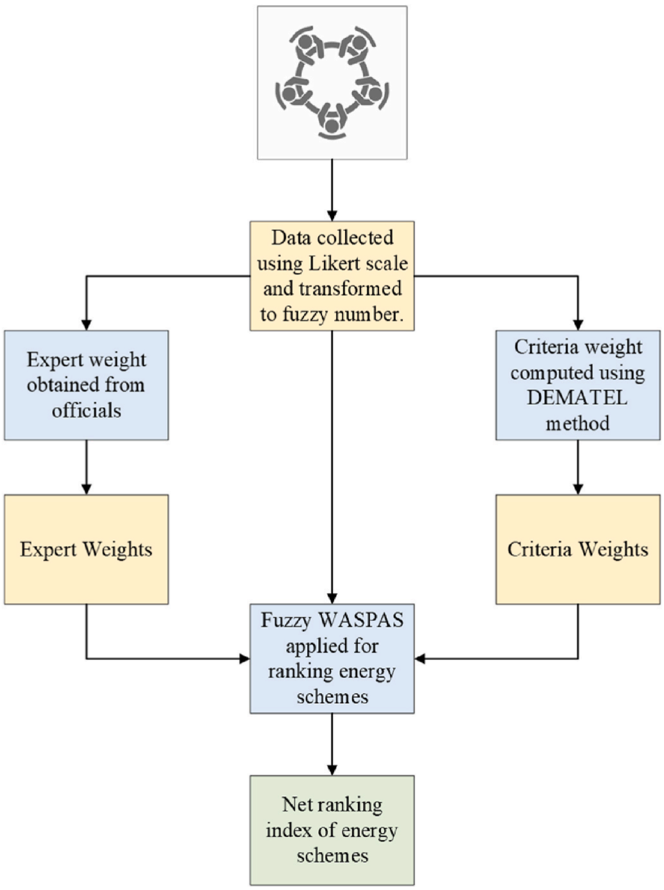

Fig. 1. Flowchart of the proposed approach.

transformed into fuzzy numbers based on the pre-determined value set, and the decision matrices are prepared for the calculation. Experts' weights are assigned with attitudinal traits mapped to the weight context by officials who invited the experts to the decision panel. Criteria are rated pairwise, and the F–DEMATEL–W is performed to determine the weights of the criteria. Individual expert-wise and cumulative weight vectors are determined and fed to the ranking module and the preference matrices to estimate the rank value of each energy scheme. The F–WASPAS approach is then applied in a fuzzy context with a weighted geometric operator for data fusion from experts. Finally, a ranking vector is obtained to order alternative policies.

To understand the mathematical construct of the model, the authors present the following points. Each expert in the panel provides their rating on the criteria and alternatives (smart grid investment) based on the criteria, which forms n × n matrices and m × n matrices. Using the weight calculation procedure and the n × n rating information, a 1 × n vector is obtained, which is the weight vector of the criteria. Likewise, the ranking procedure utilizes m × n matrices and the 1 × n criteria weight vector to determine the rank order of the smart grid investments (alternatives), which provides a vector of 1 × m.

Before presenting the step-by-step method for determining the decision parameters, i.e., the weight of criteria and rank values of alternatives (smart grid investment in this research), the rationale for the selection of fuzzy sets is provided as preference information. This work uses the F-DEMATEL-W methodology to determine the criteria weights, whereas F-WASPAS is performed to decide the rank values of smart grid investment. FST is a classical theory that models uncertainty through a single dimension, i.e., membership grade, which is considered the degree of preference in multi-criteria decision-making MCDM. Though recent studies on uncertainty have developed different variants of the FST, practitioners' simplicity and direct practical adoption of decision problems facilitated its selection in this research study. Besides, since not all stakeholders are inclined in the mathematical domain, the authors attempted to develop a ready-to-use decision tool that can cater to diverse stakeholders based on practical difficulty. So, the methodology is confined to the classical FST, which is simple, elegant, and straightforward. When it comes to criteria, any MCDM problem has different criteria, and their importance/weights are not equal. A systematic approach has been put forward to reduce bias and subjectivity in weight assignment for each criterion. DEMATEL method is considered with fuzzy preferences for determining the weights/importance of criteria. Apart from lowering bias and subjectivity, DEMATEL also (i) has simple steps/mechanisms that enable effective adoption by stakeholders; (ii) works based on pairwise comparison data, which is considered simple for elicitation and understanding; and (iii) causality relationship can be witnessed among criteria. Besides these merit points, the proposed framework embeds experts' attitudinal traits into the DEMATEL formulation for rationalizing criteria weights, including determining individualistic weights and cumulative weight vector. Towards the end, the alternatives are ranked with the view of considering minimum decision parameters to reduce the overhead of optimal parameter setting, which is an issue in other ranking approaches, such as TODIM (an acronym in Portuguese for iterative multi-criteria decision-making), combinative distance-based assessment (CODAS), combined compromise solution (CoCoSo), and so on. In sum, the novelties of the proposed framework are: (i) the importance of the criteria can be methodically decided by considering pairwise interactions and weights of experts, (ii) both individualistic expert-based weight vector and cumulative weight vector of indicators can be decided; (iii) alternatives can be ranked with minimum decision parameters.

3.1. *The proposed F–DEMATEL–W model for determining the criteria weights*

Criteria are crucial in MCDM and practical decision problems, generally from diverse categories with trade-offs and competition [31]. Naturally, the relative importance of each criterion varies significantly, and it is crucial to reflect on this phenomenon for rational decision-making [32]. Criteria weights are determined either without any priori information or with some partial information [33]. The latter puts an overhead of considering the partial information into the formulation. In the former, such information is not available. The former situation is often expected as the experts may not have a priori information [34]. Considering the situation, some methods have been presented in both categories. Some popular techniques are AHP and entropy in the former and optimization models in the latter.

DEMATEL is a popular approach in the former category that has gained much attention [35]. The superiorities of DEMATEL are [36]: (i) it is simple and elegant; (ii) it provides importance values along with the cause-effect relationship among criteria; and (iii) pairwise interaction is considered among the criteria set. These features motivated the authors to facilitate the approach used in the study. Considering the presented merit points, the proposed formulation considers each expert's criteria type and attitudinal traits. They are also potential parameters in the decision process. Thus, considering these aspects in the proposed formulation, a novel extension of DEMATEL is presented. Besides, the expert-wise weight of criteria is also derived, allowing policymakers and experts to know the criteria better from the individual's perspective. Specifically, DEMATEL converts the cause-effect relationship to an intelligible structural model [37]. improved DEMATEL to make the working procedure elegant. Some of the noteworthy ameliorations are presented as follows.

Definition 1. A direct relationship between two entities is not symmetric, and a $n \times n$ pairwise comparison matrix is obtained with an entry a_{ij} representing the degree to which criterion j affects criterion i. The prime intention of the value is to define the influence and direction with an outcome as $A = [a_{ij}]_{n\times n}$.

Definition 2. An expert provides her/his rating based on the pairwise comparison of criteria, and so e matrices of $n \times n$ order are obtained, upon which the steps are incorporated.

Definition 3. Each expert possesses an attitudinal trait that affects the rating of entities and the decision process. Attitudinal values are mapped to the unit interval, with 0.50 being the mid value, less than 0.50, and greater than 0.50 being the two categories. Concerning the attitudinal value, 0.50 refers to a neutral attitude, less than 0.50 is risk-averse, and greater than 0.50 is risk appetite.

Consequently, the step-by-step procedure for weight calculation is presented below.

Step 1 Consider pairwise rating of criteria from each expert, which forms e matrices of $n \times n$ order. Note that the Likert scale is used for rating criteria.

Linguistic term-based rating is adopted with a seven-Likert scale by considering terms such as very bad (VB), a little bad (ALB), bad (B), medium (M), good (G), a little good (ALG), and very good (VG) with fuzzy values as 0.10, 0.20, 0.30, 0.40, 0.50, 0.60, and 0.70, respectively [38].

Step 2 Transform the qualitative rating to fuzzy values and normalize the matrix from each expert using Eq. (1).

$$N = \frac{u_{pq,k}}{max_i\left(\sum_j u_{pq,k}\right)} \quad \forall p,q \in n \tag{1}$$

where $u_{ij,k}$ is the fuzzy value from expert k for any criterion p compared over any criterion q.

Afterward, the transformation is performed. It should be noted that the criteria set must be homogenized before applying Eq. (1), meaning that all criteria are made to be of a single type, either benefit or cost. Herein, all criteria are converted to benefits. The negation operation of fuzzy numbers is performed to homogenize the rating information. Eq. (1) gives the normalized matrix for each expert, which is given to the following step for relational value determination. It must be noted that the values in N are also of order n × n. The denominator of Eq. (1) considers the maximum value of the net criterion value, and that value is used as a divisor of every element in the pairwise comparison matrix by a particular expert.

Step 3 Determine each expert's relational criteria values using Eq. (2). $n \times n$ relational values are obtained for each expert.

$$T = N^*(I - N)^{-1} \tag{2}$$

where * is matrix multiplication and I is the identity matrix, $(.)^{-1}$ is the inverse of a matrix.

It must be noted that Eq. (2) yields an n × n matrix, which represents the relational value of each expert associated with the decision process. Specifically, there are e matrices of n × n that are obtained. The inverse function that determines the inverse of a matrix obtained after subtracting the normalized matrix from the identity matrix forms an n × n matrix multiplied by the normalized matrix and yields an n × n matrix. Here, multiplication refers to matrix multiplication and identifies a matrix with diagonal entries as "1" and others as "0".

Step 4 Determine the row and column sum by applying Eqs. (3) and (4). Row and column vectors of $1 \times n$ each are obtained for each expert.

$$R_p = \sum_p T_{pq,k} \tag{3}$$

$$C_q = \sum_q T_{pq,k} \tag{4}$$

where R_p and C_q are the row and column sums, respectively.

Based on Eqs. (3) and (4), the row-wise and column-wise sum vectors are obtained, which forms a vector of 1 × n order. Specifically, the two vectors are used to determine the criteria weights and the causality among criteria.

Step 5 Add the two vectors from Eqs. (3) and (4) to determine the significance vector, which is normalized by using Eq. (5) to determine the weight vector of criteria for each expert.

$$W_{j,k} = \frac{R_p + C_q}{\sum_n (R_p + C_q)} \tag{5}$$

where $W_{j,k}$ is the weight of criterion j based on the rating from expert k.

It must be noted that Eq. (5) provides a weight vector of 1 × n order for each expert. Suppose there are e experts, then e vectors of 1 × n order are obtained. This represents the criteria weights from an individual expert's point of view.

Step 6 Determine the cumulative weight vector by considering the attitudinal value of the expert and the weight vector from Eq. (5). Eq. (6) is applied to determine the cumulative criteria weights.

$$W_j = \prod_{k=1}^{e} (W_{j,k})^{\lambda_k} \tag{6}$$

where W_j is the weight of criterion j, e is the number of experts, *and* λ_k is the attitudinal value associated with an expert k.

Eq. (6) calculates the cumulative weights of criteria, a single vector of 1 × n order. W_j is calculated by considering weight vectors from Eq. (5) and experts' weights. The attitudinal trait is in the unit interval; a value less than 0.50 is considered risk averse, a value greater than 0.50 is considered risk appetite, and a value of 0.50 is considered neutral. Value from Eq. (6) is also in the unit interval with sum leading to unity. Likewise, the traits of experts are also in the unit range with a sum equal to unity.

3.2. F–WASPAS for ranking of the alternatives

Ranking is an essential phase in MCDM that gives an ordering of alternatives to help experts and policymakers decide the suitable alternative for the specified task or job. Based on the rating data from experts and weights of criteria, ranking approaches determine the rank values of each alternative, and they order the alternatives based on these values. During the ranking process, a utility measure is applied to the rating information from experts to gain a rank value associated with each alternative, which can be further ordered based on the value for selecting the appropriate option from the family of options for a specified task or job.

WASPAS is a ranking approach that uses a linear combination of weighted sum and product. Besides, the superiorities of WASPAS are [39]: (i) it is straightforward and elegant, (ii) it takes strategy values of experts into account during rank estimation, and (iii) ranking is done via the sum/product utility measures. WASPAS works based on the weighted sum and weighted product utility functions. These two functions are applied to each alternative over the criteria set with the weights of criteria considered as a vector. Specifically, an $m \times n$ decision matrix consisting of preference data from each expert is considered along with a criteria weight vector of $1 \times n$ order. Notably, these values are given as input to the procedure for determining the rank values of alternatives, which would eventually form a $1 \times m$ vector ordered to obtain a suitable alternative for the desired task or job based on the set of alternatives.

In the formulation, the two utility functions are independent rank estimation modules combined based on the Lagrangian multiplier that mimics the strategy values adopted by the experts. The multiplier is in the unit interval, and a value of 0.50 is neutral; less than 0.50 will weigh the product function more and the sum function less, whereas a value greater than 0.50 will weigh the sum function more and the product function less. During the formulation, it is worth noting that the weighted product function yields values less than or equal to the weighted sum function [40].

Lemma 1. *If w_j $\forall j = 1, 2, \ldots, n$ is the weight vector with all values of the vector in the unit interval and $\sum_j w_j = 1$, then $\prod_{j=1}^{n} a_i^{w_j} \leq \sum_{j=1}^{n} w_j.a_i$.*

The step-by-step procedure for the rank calculation of investment schemes related to the energy domain is as follows.

Step 1 Expert rating information on each energy investment alternative is considered based on the criteria set. Qualitative rating via the Likert scale is adopted and transformed into fuzzy numbers based on pre-defined values. e matrices of order m × n are obtained. Based on the conversion value presented in Section 3.1, the decision matrices from experts are converted, and fuzzy rating information is obtained, which forms e matrices of $m\times n$ order.

Step 2 Expert decision matrices are aggregated using Eq. (6). Later, ranking parameters, i.e., weighted sum and weighted product, are determined using Eqs. (7) and (8). Thereby, two vectors of $1 \times m$ are obtained.

$$M_i = \sum_{j=1}^{n} W_j.u_{ij} \tag{7}$$

$$D_i = \prod_{j=1}^{n} (u_{ij})^{W_j} \tag{8}$$

where u_{ij} is the aggregated fuzzy rating information for scheme i regarding criterion j.

The aggregated matrix obtained via Eq. (6) is provided in Eqs. (7) and (8) for determining the weighted sum and weighted product vectors, each of order 1 × m. Notably, from Lemma 1, values from Eq. (7) are greater or equal to values from Eq. (8). Since both vectors are utilized for ranking alternatives (smart grid investment), they are considered for determining the net rank value.

Step 3 Calculate the net rank value of investment schemes by applying Eq. (9). A vector of 1 × m is arranged in descending order to get the ordering of energy investment schemes.

$$K_i = \alpha.M_i + (1-\alpha).D_i \tag{9}$$

where α is the strategy value in the unit interval.

Based on the values from Eq. (9), investment policies are ordered. A higher rank value implies a high preference, and so on. This means that Eq. (9) values are arranged in descending order. Based on the two utility functions from Eqs. (7) and (8), the net ranking is obtained (refer to Eq. (9) for clarity).

Lemma 2. *If α is the Lagrangian multiplier in the unit range, then M_i increases in comparison to D_i when $\alpha > 0.50$, but when $\alpha < 0.50$, M_i decreases compared to D_i.*

4. Evaluating smart grid investments by F–DEMATEL–W–WASPAS methodology

This research aims to evaluate smart grid investments by creating a novel fuzzy group decision-making model. Twelve indicators concerning the literature review results are selected in the first stage. The descriptions of the criteria utilized in the research are as follows.

Transmission efficiency (C1): With the help of improved transmission efficiency, energy losses can be minimized. This situation has a positive influence on the increase in reliability of electricity delivery.

Leveraging digitalization (C2): Digital technologies allow quick obtaining of necessary data. Therefore, more critical evaluations can be performed by using data. To achieve this objective, smart grid companies should prioritize improving technological investments.

Grid infrastructure upgrades (C3): Strengthening the technological infrastructure contributes to the more successful operation of these systems. Advanced technological systems help to ensure fewer disruptions in these processes. Also, possible problems can be detected early with the help of advanced technological processes.

Cyber security (C4): Owing to cyber security, it is possible to prevent possible technological attacks on the project's IT systems. This system contains private information about many customers. If this information falls into the hands of unauthorized persons, significant customer dissatisfaction occurs. Therefore, smart grid investors must take the necessary precautions to ensure cybersecurity.

Enabling demand response (C5): To increase the success of these investments, the supply and demand balance must be analyzed correctly. If there is insufficient demand for these products in the market, new investments will not succeed.

Financial viability (C6): Smart grid investments require many financial resources. With the help of financial viability, it can be much easier to find financial capital for these projects. This situation positively contributes to increasing the effectiveness of smart grid investments.

Load balancing (C7): Load balancing is crucial for increasing the effectiveness of smart grid investments. Owing to this situation, grid stability can be provided. In addition to this issue, uninterrupted electricity production can be maintained.

Competitive market conditions (C8): Market conditions are critical for smart grid projects to be more successful. In this context, the profit margin is low in a competitive market. Therefore, investors become reluctant to invest in the markets.

Regulatory framework (C9): Legal regulations must be prepared effectively for smart grid investments to perform well. In this way, investors' confidence in the market increases. This supports the development of smart grid projects.

Customer awareness (C10): To increase the performance of smart grid projects, customers' expectations must be met. Expectations may vary for different customer groups. Therefore, meeting these expectations increases customer satisfaction.

Use of technological innovations (C11): Technological developments help minimize project costs. Owing to this condition, the profitability of the investments can be increased. Hence, it is possible to increase the effectiveness of these investments.

Integration of renewables (C12): The development of smart grid projects also increases the use of renewable energy. Reducing costs significant for renewable energy projects, such as energy storage, is possible in these projects. Thus, the use of clean energy will be more profitable.

Moreover, the alternative policies for renewable energy projects are as follows.

Pricing guarantees with the fixed payment rate (A1): Since there is a guarantee for fixed income, this situation attracts the attention of the investors. With the help of this issue, smart grid investments can be increased.

Exchanging the surplus electricity from the system owners (A2): It is paramount to ensure the balance of supply and demand for electricity production and consumption. Otherwise, production over demand negatively affects the effectiveness of the projects. Correctly utilizing these surpluses contributes to increasing profitability.

Trading the electricity with eco-energy certificates (A3): Eco-energy certificates can facilitate businesses' commercial processes. These certificates positively increase the image of businesses. The products of companies with such certificates attract the attention of customers who are especially sensitive to environmental issues. Thus, businesses are preferred by customers more.

Encouraging sustainable energy production using financial incentives (A4): The costs of smart grid investments are very high. Therefore, high financing is needed to ensure the return on these investments. Government incentives also contribute significantly to this process.

The rating scale and its fuzzy value are provided here. As mentioned earlier, a seven-Likert scale by considering terms such as very bad (VB), a little bad (ALB), bad (B), medium (M), good (G), a little good (ALG), and very good (VG) with fuzzy values as 0.10, 0.20, 0.30, 0.40, 0.50, 0.60, and 0.70, respectively [38].

The steps for calculating the ranks of alternative policies for renewable energy projects are as follows.

Step 1 Consider rating from four experts in the qualitative form via Likert scales to rate four energy investment schemes based on twelve criteria. Four decision matrices are formed in order 4×12 (Table 2).

Step 2 Obtain rating information on criteria to form a 4×12 weight assessment matrix as presented in Table 3.

Step 3 Applying the procedure in Section 3.1 to calculate the criteria weights. Eqs. (2)–(4) are applied to determine the parameters of the criteria weights. The row-wise summed vector and the column-wise summed vector are obtained from these equations fed to Eq. (5) for weight determination of criteria from each expert.

To obtain criteria weights, Eq. (2) is applied to determine the relational values of criteria, and it is depicted in Fig. 2 (a) to Fig. 2 (d). Based on these values, row sum, and column sum are determined for each expert, and so 1×12 vectors for row/column are determined via Eqs. (3) and (4), which is fed to Eq. (5) for criteria weight determination based on the pairwise values/rating given by each expert. The net weight vector is determined using Eq. (6), and the attitudinal values of experts are considered as 0.20, 0.30, 0.30, and 0.20, respectively. Based on the values from Fig. 2(a)–(d), weights of criteria are determined as 0.077 (C1), 0.085 (C2), 0.069 (C3), 0.095 (C4), 0.087 (C5), 0.090 (C6), 0.085 (C7), 0.089 (C8), 0.091 (C9), 0.073 (C10), 0.079 (C11), and 0.075 (C12), respectively. More clearly, cyber security (C4; 0.095) is the foremost driver, followed by regulatory framework (C9; 0.091), financial viability (C6; 0.090), and competitive market conditions (C8; 0.089).

Step 4 Based on the rating information in Step 1 and the weight vector from Step 3, rank values are determined by applying the procedure in Section 3.2. Table 4 depicts the parameter's weighted sum (M_i), weighted product (D_i), and each scheme's net rank value (K_i).

Based on the values in Tables 4 and it is inferred that the ordering of the energy investment scheme is A4 > A2 > A3 > A1. Consequently, "encouraging sustainable energy production using financial incentives" (A4) is the most suitable policy choice from the other potential policies, followed by "exchanging the surplus electricity for the system owners" (A2). To get the final ranking, Eqs. (7) and (8) are applied to determine the weighted sum and weighted product values associated with each policy, which is further utilized by Eq. (9) to determine the rank values of the policies. In Table 4, the net rank value is calculated for $\alpha = 0.50$.

4.1. Sensitivity and comparative analyses

This section focuses on understanding the merits of the developed

Table 2
The alternative policies for renewable energy projects.

Policies	Criteria											
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
	DM1											
A1	VG	M	M	ALG	G	ALG	ALB	M	G	M	ALB	G
A2	M	ALG	B	G	G	G	G	G	G	ALG	G	G
A3	ALG	M	M	G	ALG	G	ALG	M	VG	G	G	G
A4	VG	G	M	G	ALG	ALG	ALG	G	VG	G	G	VG
Policies	Criteria											
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
	DM2											
A1	VG	M	M	ALG	G	ALG	B	M	G	M	M	M
A2	M	M	B	VG	VG	G	M	G	VG	M	M	ALB
A3	ALG	M	M	ALB	ALG	G	ALG	M	VG	G	ALB	ALB
A4	VG	G	M	G	ALG	ALG	ALG	G	M	M	VG	M
Policies	Criteria											
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
	DM3											
A1	VG	M	M	ALG	G	ALG	B	M	G	M	ALB	G
A2	M	ALG	B	G	G	G	G	G	G	ALG	M	G
A3	ALG	ALB	M	ALB	ALG	G	ALG	M	VG	G	M	ALB
A4	ALB	G	M	G	ALG	ALG	ALG	M	M	G	M	VG
Policies	Criteria											
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
	DM4											
A1	VG	M	M	ALG	G	ALG	ALB	M	G	M	B	M
A2	M	ALG	B	G	G	G	G	G	G	ALG	G	M
A3	ALG	M	M	VG	ALG	G	ALG	B	VG	G	VG	ALB
A4	ALB	G	M	VG	ALG	ALG	ALG	G	VG	G	G	ALB

Table 3
The criteria set for smart grid investment decisions.

Criteria	Max	Max	Max	Max	Max	Max	Max	Max	Max	Max	Max	Min
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
	DM1											
C1		M	ALB	G	ALB	ALG	ALB	ALB	ALG	M	G	VG
C2	M		ALG	VG	ALG	G	M	G	M	ALB	G	ALG
C3	ALB	M		B	ALB	B	ALB	ALG	M	G	G	G
C4	G	G	M		G	VG	VG	VG	VG	G	VG	VG
C5	ALG	G	M	G		G	G	G	VG	ALG	G	G
C6	G	G	ALG	VG	G		VG	G	ALG	ALG	G	G
C7	G	G	ALG	G	G	G		G	G	ALG	G	G
C8	VG	VG	M	VG	G	G	G		ALG	M	VG	VG
C9	VG	G	G	G	VG	VG	ALG	ALG		G	G	VG
C10	M	M	VG	G	ALB	ALB	ALB	ALG	M		M	G
C11	G	G	M	G	G	G	G	VG	ALG	ALB		ALG
C12	M	G	ALB	ALG	G	G	M	VG	VG	M	G	
Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
	DM2											
C1		M	G	G	ALB	ALG	ALB	ALB	ALG	M	G	VG
C2	M		ALG	VG	ALG	G	M	G	M	ALB	G	G
C3	ALB	M		B	ALB	B	ALB	G	M	G	G	G
C4	G	G	M		G	VG	VG	VG	VG	G	G	VG
C5	ALG	G	M	G		G	G	G	VG	ALG	G	VG
C6	G	G	ALG	VG	G		VG	M	ALG	ALG	G	VG
C7	G	G	ALG	G	G	G		G	G	ALG	G	VG
C8	VG	VG	ALB	VG	G	G	G		ALG	ALB	VG	VG
C9	VG	G	G	G	VG	VG	ALG	ALG		G	G	VG
C10	M	M	VG	G	ALB	ALB	ALB	ALG	M		M	G
C11	G	G	M	G	G	G	G	VG	ALG	ALB		ALG
C12	M	ALB	ALB	ALG	VG	G	M	VG	VG	M	G	
Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
	DM3											
C1		M	ALB	G	ALB	ALG	ALB	ALB	ALG	M	G	VG
C2	M		ALG	VG	ALG	G	M	G	M	ALB	G	ALG
C3	ALB	ALG		B	ALB	B	ALB	ALG	M	G	ALG	G
C4	G	G	M		G	VG	VG	VG	VG	G	VG	VG
C5	ALG	G	M	G		G	G	G	VG	ALG	G	G
C6	G	G	ALG	VG	G		VG	G	ALG	ALG	VG	VG
C7	M	M	ALG	G	G	G		G	G	ALG	VG	VG
C8	VG	VG	M	VG	G	G	G		ALG	M	VG	M
C9	VG	G	G	G	VG	VG	ALG	ALG		M	M	VG
C10	M	M	VG	G	ALB	ALB	ALB	ALG	M		M	G
C11	G	ALG	M	G	G	G	G	VG	ALG	ALB		ALG
C12	M	G	ALB	ALG	G	G	M	VG	VG	M	G	
Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
	DM4											
C1		M	ALB	G	B	ALG	ALB	ALB	ALG	M	G	VG
C2	M		ALG	VG	ALG	G	ALG	G	M	ALB	G	ALG
C3	B	M		B	ALB	B	ALB	ALG	M	G	ALG	G
C4	M	M	M		G	VG	VG	VG	VG	G	VG	VG
C5	M	M	M	G		G	G	G	VG	ALG	G	G
C6	G	ALG	ALG	VG	G		VG	B	ALG	ALG	G	G
C7	G	G	ALG	G	VG	VG		B	G	ALG	G	G
C8	VG	VG	B	M	M	M	G		ALG	B	VG	VG
C9	VG	G	G	G	VG	VG	ALG	ALG		G	M	M
C10	M	M	VG	G	ALB	ALB	ALB	ALG	M		M	G
C11	G	G	M	G	G	G	G	VG	ALG	ALB		M
C12	M	G	ALB	ALG	G	G	M	VG	VG	M	G	

model from the point of view of variation of weights of criteria and strategy values. Strategy values are varied with unit step size from 0.10 to 0.90 to understand the impact of the strategy values on rank orders given a set of criteria weights. Inter-sensitivity and intra-sensitivity analyses are conducted based on the variation of criteria weights and strategy values, respectively. To this end, biased and unbiased weight types are considered for criteria, where the biased type refers to weights of criteria determined via Section 3.1, whereas the unbiased type is the assignment of equal weights to all criteria. This value in the study is 0.083, obtained from assigning 1/12 as weight values for all criteria.

From Fig. 3, it is evident that the proposed model is highly robust in altering strategy values, as the rank order remains unchanged for different strategy values. However, there is a change in rank values for alternative policies. Furthermore, when an unbiased weight type is adopted, a change in the ordering of alternative policies for different strategy values can be observed, indicating the robustness is compromised when an equal or unbiased weight type is utilized. Intuitively, it is inferred that the criteria weights are unequal due to competition and trade-offs. As a result, equal weights are not rational, and the ordering changes, pointing out that the robustness is affected when equal weights are considered. During inter-sensitivity analysis, the rank orders change due to changes in criteria weights, and it is intuitively regarded as

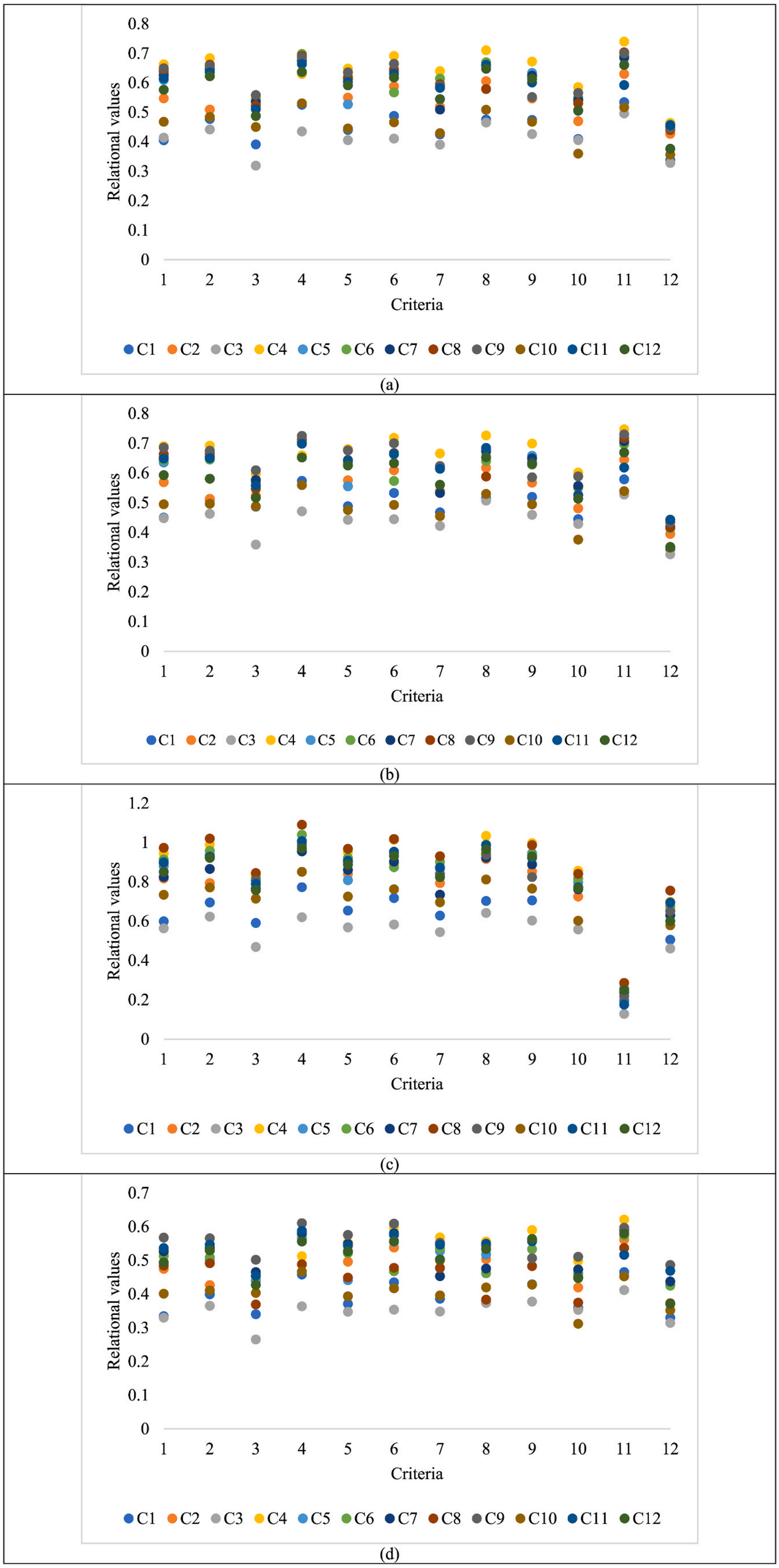

Fig. 2. Relational values for each expert (a is DM1, b is DM2, c is DM3, and d is DM4).

Table 4
Rank parameter values of each smart grid investment scheme.

Scheme	M_i	D_i	K_i	Rank
A1	0.461	0.445	0.453	4th
A2	0.515	0.499	0.507	2nd
A3	0.476	0.466	0.466	3rd
A4	0.520	0.518	0.517	1st

natural with the inference that weights of criteria are crucial for rank determination.

Beyond understanding the theoretical efficacy, the proposed model is compared with extant energy-related decision models. In this regard, recent models, such as [41–43], are compared with the proposed framework. Table 5 provides the summarized view of the feature-based comparison.

In sum, some innovative features of the proposed framework include.

- The fuzzy number is considered preference information that allows experts to use the pre-determined qualitative terms as rating information based on singleton membership function, providing straightforward understanding to stakeholders about their data. The conversion mechanism is simple and elegant compared to other variants.
- Criteria interactions are captured based on the pairwise comparison that allows experts to consider every pair of criteria without explicitly excluding any criterion. Experts gain comfort in rating entities pairwise as their cognitive thought pertains to a specific pair at a given time. Though there is computational overhead, the ease and effectiveness of the rating process are promising and attractive.

Table 5
Highlights of proposed and extant frameworks towards sustainable energy-based investment decisions.

Features	Proposed	[41]	[42]	[43]
Data	Fuzzy	Fuzzy	Variant	Variant
Criteria interaction	Considered	Considered	No	No
Weight type	Objective	Objective	Objective	Subjective
Personalized weight	Calculated	No	No	No
Experts' importance	Considered	No	No	No
Rank type	Utility	Utility	Utility	Utility

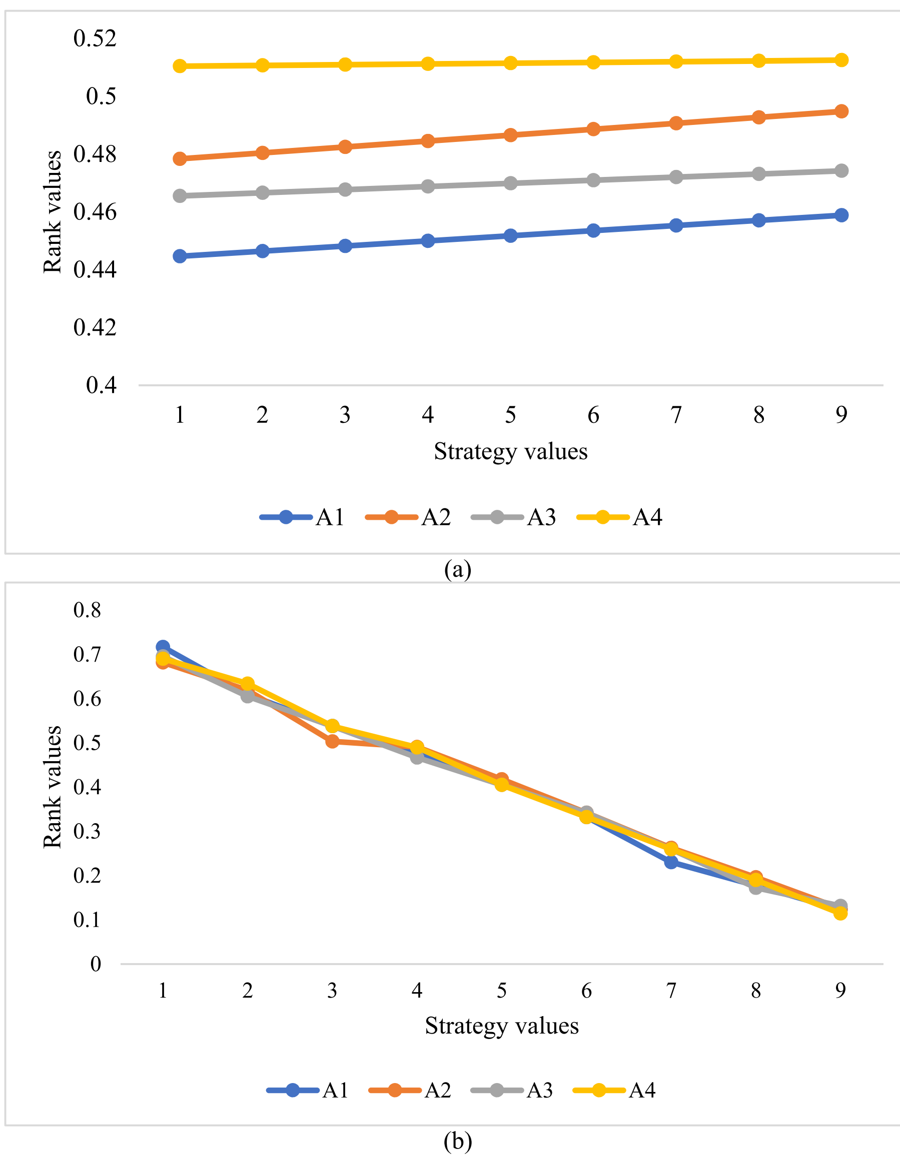

Fig. 3. Sensitivity analysis of criteria weights and strategy values – inter and intra type (a is unequal criteria weights and b is equal criteria weights; X axis labels 1 to 9 denote values 0.1 to 0.9, respectively).

- The personalized weight vector is calculated based on each expert's pairwise rating, which is further fused to obtain the cumulative importance vector of criteria. Specifically, the experts' attitudinal traits are embedded in the formulation to determine the cumulative weight vector of the criteria. The attitudinal characteristics are modeled in the unit interval with values less than 0.50 denoting risk aversion trait, greater than 0.50 denoting risk appetite trait, and equal to 0.50 denoting neutral trait.
- F–WASPAS approach is utilized with fuzzy rating data to rank the alternative policies by considering the cumulative criteria weight vector. The approach is easy and effective, with minimum parameter requirements for decision-making. Compared to other methods, such as TODIM [41], CoCoSo [44], and so on, the proposed model requires minimum decision parameters for determining the rank ordering of alternative policies for renewable energy projects.

From a statistical aspect, models like [45–47] are compared with the proposed model by feeding the data from Section 4 into each framework to determine the rank values and order of energy investment schemes. Spearman correlation is applied to determine the consistency coefficient of the methods, and the result infers that the proposed model is consistent with other models.

The proposed integrated approach utilizes fuzzy set theory, considered a simple but elegant way to represent uncertainty that practitioners can adopt effectively. The model intends to reduce subjective randomness and human intervention, achieved by methodical calculation of decision parameters. The weights of indicators are methodically determined by considering the weights of experts and the pairwise interactions between indicators. Expert-wise criteria weight vectors and cumulative weights for indicators are defined to provide the relative importance of each indicator and influence the ranking of energy policies. Since experts are considered crucial in the decision process, associating their attitudinal characteristics with unit interval weights is essential, and embedding those values in the formulation enhances the rationality of the decision process. Driven by the inference, in this proposed approach, F–DEMATEL–W considers pairwise interactions and experts' weights that are being mapped to the attitudinal behavior of experts that rationally influence the ordering of alternatives (here, energy policies). Specifically, the weight values less than 0.50 to experts are considered to be risk avoiders who potentially look for safe alternatives or alternatives with better performance in the benefit criteria/indicators zone. Typically, these experts do not prefer experimenting with unusual choices but rather go by the rule of thumb: the better an alternative for maximizing criteria type, the higher the priority. In contrast, the experts with weights greater than 0.50 are risk takers and prefer experimenting with those alternatives whose maximizing type criteria ratings are not so good and focus on minimizing criteria type. Once the value is exactly 0.50, the experts are neutral in their choice-making. Rating data from experts are aggregated consistently with each expert's rating and weights of experts. Afterward, the rank values for the policies are determined with the help of cumulative weight vectors obtained via the weight fusion process by obtaining weight vectors of criteria from each expert and weights of experts.

Finally, some advantages of the approach are: (i) the developed model is simple but elegant; (ii) it is practitioner-friendly and methodical with reduced subjective randomness and bias; (iii) decision parameters are methodically determined with not only values but also the cause-effect relationship study and straightforward rank values for ordering policies effectively; (iv) pairwise interactions of criteria and attitudinal trait mapped with experts' weights are considered during indicators' weight determination process; and (v) rank values of alternatives are determined with minimum decision parameters that aid practitioners and policymakers to utilize the method with little mathematical background effectively and can effectively conclude inferences compared to other extant models.

5. Discussion and implications

This research evaluates alternative policies for renewable energy projects concerning smart grid investment factors through a novel fuzzy group decision-making tool. Regarding the findings, the significance weights of the determinants of smart grid investments are as follows: financial viability (C1; 0.092), leveraging digitalization (C2; 0.083), cyber security (C3; 0.097), grid infrastructure upgrades (C4; 0.073), enabling demand response (C5; 0.081), transmission efficiency (C6; 0.078), load balancing (C7; 0.083), integration of renewables (C8; 0.077), customer awareness (C9; 0.077), regulatory framework (C10; 0.094), use of technological innovations (C11; 0.075), and competitive market conditions (C12; 0.086). Thus, cyber security is the foremost driver, followed by regulatory framework, financial viability, competitive market conditions, leveraging digitalization, load balancing, enabling demand response, transmission efficiency, integration of renewables, customer awareness, use of technological innovations, and grid infrastructure upgrades.

Cyber security must be sufficient to increase the effectiveness of smart grid investments. Smart grids are projects with very comprehensive and complex structures. Therefore, necessary precautions must be taken against cyber-attacks. Otherwise, power outages may occur as a result of these attacks. This situation negatively affects the performance of the projects. Cyber security is vital in ensuring the effectiveness of smart grid investments. A cyber-attack on the infrastructure of these projects may cause disruptions in the energy distribution process. This situation causes severe economic losses as it will cause energy outages. Any negativity that may occur in the security of the smart grid infrastructure makes customers uneasy. The occurrence of customer dissatisfaction negatively affects the performance of these projects. Alsuwian et al. [48] identified that cyber security is paramount in ensuring customer data security. Inadequate cyber security may cause this data to fall into the hands of malicious individuals. Li and Yan [49] determined that this situation causes customers' trust in the projects to decrease. It is essential to take these security measures to prevent customer dissatisfaction. Otherwise, Mohammed and George [50] determined that businesses will seriously lose competitiveness. Smart meters allow these networks' energy production and consumption data to be instantly monitored. Massaoudi et al. [51] and Yu et al. [52] concluded that a possible cyber-attack causes disruptions in this process. This situation negatively affects the performance of the projects.

Legal procedures should also be sufficient to increase the effectiveness of smart grid investments. Adequate legal regulations provide significant confidence to investors. This situation allows more investors to focus on these projects. Thus, it becomes possible to increase smart grid investments. Ahmad et al. [53] defined smart grid projects as involving sensitive issues such as collecting customer data. Roomi et al. [54] and Park et al. [55] demonstrated that it is essential for the security of the process that these data fall into the hands of unauthorized persons. Therefore, adequate legal regulations increase investors' confidence in these projects. Raza et al. [56] indicated that competitive conditions in the market must function for investors to focus on smart grid projects. Ayub et al. [57] concluded that effective legal regulations increase investors' confidence. Thus, it becomes possible to increase smart grid investments.

Further, regarding the findings, "encouraging sustainable energy production using financial incentives" is the most essential policy for renewable energy projects. The findings align with the available studies (e.g., Refs. [58–60]) and can contribute to the ongoing discussion on designing renewable energy policies. Smart grid infrastructure may have higher costs than traditional energy infrastructure due to the need for energy storage. Financial incentives can contribute to investors' focus on these projects in this context. Thanks to incentives such as low-interest loans and tax deductions, the costs of projects can be reduced. This situation can increase the profitability of investments. Additionally, financial incentives can support the development of innovative technologies. This allows the smart grid infrastructure to be continuously improved. Providing financial incentives for these projects is necessary for developed and developing countries. The most significant disadvantage of these projects is that the initial costs are very high. Since this situation makes investors nervous, they may be reluctant to participate in these projects. Therefore, this high-cost problem must be resolved to ensure the sustainability of these projects. This is a crucial issue independent of the countries' economic power. In this context, countries with high economic power should also provide financial incentives to these projects, just like emerging economies. This makes a solid contribution to managing costs more effectively.

6. Conclusion

This study aims to evaluate alternative policies for renewable energy projects regarding smart grid investments by developing a novel fuzzy group decision-making model. Regarding the literature review results, twelve drivers are selected in the first stage. These factors are then examined via the F–DEMATEL–W methodology. Finally, four alternative policies are ranked with the help of F–WASPAS. It is concluded that cyber security is a paramount issue in increasing the effectiveness of smart grid investments. Similarly, sufficient legal procedures are further significant in this respect. Moreover, the ranking results demonstrate that encouraging sustainable energy production using financial incentives is the foremost alternative policy. Note that exchanging surplus electricity for system owners is another essential alternative to this situation. A comprehensive sensitivity and comparison analysis prove the introduced framework's robustness and effectiveness. Some applications can be considered to increase cyber security in smart grid investments. Strong encryption can minimize the risk of unauthorized persons accessing it. Using antivirus programs is essential to detect and prevent malicious software. Similarly, smart grid infrastructure staff and users should be trained on cybersecurity risks. This is necessary to increase security awareness among employees.

The possibility that the findings may change in a similar study conducted with a team of different decision-makers is one of the most critical limitations of the study. As expected, one expert's knowledge, experience, and judgment may differ from another. Further, some methodology-oriented limitations are: (i) experts' weights are directly assigned that might incur a certain level of bias and subjectivity within the decision system; (ii) partial information regarding entities cannot be formulated in the presented system; and (iii) one-dimensional fuzzy modeling is adopted with the view of ease of practical utilization. In the future, plans are made to address the limitations of the work. The proposed model is used for different energy-related applications, such as energy source selection, energy site selection, raw material purchase options for energy-related modules, etc. Similarly, the proposed model can be extended for different sustainability applications, medical applications, engineering applications, logistic domains, etc. Some specific target areas planned are barrier grading, hospital selection, alternative fuel effect, green vehicle selection problem, green materials selection problem, vendor/supplier evaluation, technology assessment, etc. The proposed model can also be extended to diverse fuzzy domains, such as orthopair fuzzy sets, neutrosophic sets, interval and probability variants, hesitancy domains, etc. Mobile applications for ready-made tailored decision support can be planned, integrating machine learning and recommendation paradigms. Finally, quantum features can be integrated with the decision model to extend decision application to a large-scale scenario. In addition to them, another limitation of the proposed model is that all experts' weights are assumed to be equal. However, these people can have different qualifications according to their different demographic factors. Hence, calculating the decision matrix by taking the average of these evaluations is criticized in the state-of-the-art. This situation negatively affects the quality of the analysis results. Therefore, overcoming this criticism can construct a novel model for future research direction.

CRediT authorship contribution statement

Hasan Dinçer: Methodology, Software, Validation, Investigation, Writing – original draft. **Raghunathan Krishankumar:** Conceptualization, Methodology, Investigation, Data curation, Writing – original draft. **Serhat Yüksel:** Writing – original draft, Data curation, Validation, Writing – review & editing, Visualization, Supervision. **Fatih Ecer:** Conceptualization, Visualization, Investigation, Writing – review & editing, Supervision.

Declaration of competing interest

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

Data availability

The data that has been used is confidential.

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