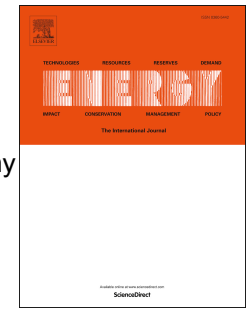
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Analysis of energy efficiency investments in smart manufacturing via double hierarchy linguistic structure-based hybrid decision-making model

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Abstract

This study examines energy efficiency investments in smart manufacturing. For this purpose, a hybrid decision framework is put forward within the double hierarchy linguistic context. The hybrid model encompasses methods for rational determination of decision parameters, viz., experts' weights, criteria weights, and ranks. The research gap in methodically determining experts' weights, along with considering the interdependencies among experts, is addressed by DHHFL-CRITIC, which utilizes correlation and variance measures to overcome this challenge. Likewise, the gap of fluctuations or spikes in preferences owing to extreme scale values is nullified through DHHFL-LOPCOW, which uses log functions to smooth spikes. Finally, the computational complexity gap during rank determination is circumvented by DHHFL-OPARA, which eliminates the normalization procedure, thereby reducing the complexity during rank determination. These methods together form the framework, and the framework analyzes investment options in energy efficiency. The findings of this study have important implications for both theory and practice. In the theoretical sense, a new model is proposed to contribute to the literature. Thanks to the latest model, reliable results can be obtained. In practical terms, a set of criteria affecting energy efficiency in smart manufacturing processes is defined, and the most optimal strategies affecting energy efficiency in these processes are identified. The analysis results with the new model show that the most influential criteria are maintenance and idle time, along with the green building design and energy monitoring system being the key options for investments to support energy efficiency with smart manufacturing.

Keywords: energy efficiency; energy investments; CRTIC method; LOPCOW approach; OPARA method.

1. Introduction

Energy efficiency indicates an increase in production volume by using less energy. This situation provides an opportunity for businesses to use their resources effectively. Energy efficiency investments in smart production indicate the sustainability of production processes. It is possible to talk about many different advantages of these investments. These projects significantly reduce energy consumption (Zheng et al., 2024). As a result of this issue, production costs can be reduced, and sustainable growth is facilitated (Pan et al., 2022). With the help of this condition, the profit margin of businesses can be increased. This situation also brings a significant competitive advantage to businesses. On the other hand, these projects also provide environmental benefits (Li et al., 2021). Less energy consumption contributes to the reduction of carbon emissions (Jin et al., 2024). This situation allows sustainable development goals to be achieved more easily. Similarly, these projects also support the less consumption of natural resources. Due to this condition, the environmental benefits of investments can be increased.

Some factors directly affect the performance of energy efficiency investments in smart production. The development of technological infrastructure is of key importance in this process. With the use of current technologies, comprehensive data on energy consumption processes can be obtained. It is possible to provide optimization by analyzing this data in detail (Chen et al., 2024). In addition to this condition, qualified personnel are also of critical importance in increasing the effectiveness of these investments. Thanks to these trainings, employees' awareness of energy efficiency can be increased. Owing to this condition, it is possible to reduce energy waste. Legal regulations also support the performance of these investments (Gajdzik et al., 2024). Energy efficiency incentives provided by governments offer significant cost advantages to investors. Moreover, the comprehensiveness of legal regulations affects the formation of standards that guide businesses.

To increase the performance of energy efficiency investments in smart production, determining the most important factors is reasonably necessary. This is very important, primarily for the efficient use of resources. Energy efficiency investments in smart production systems can be costly (Wang et al., 2024). Therefore, determining which factors are more important allows the most effective use of the budget. If the most critical factors are not determined, investments may be directed to the wrong areas, leading to a waste of resources. Therefore, which factors are more effective should be analyzed to allocate the budget most efficiently. Similarly, prioritizing the factors that will contribute the most to energy efficiency performance also supports the increase in investment performance. Determining the most important factors in energy efficiency investments guides strategic planning processes. Owing to this situation, businesses can be more successful in developing long-term strategies. The profitability of investments is directly related to the energy savings and operational efficiency increase achieved. Determining critical factors allows focusing on areas that offer the highest potential in terms of return on investment. Furthermore, determining the technologies that have the most impact on energy efficiency helps the business gain a competitive advantage in the sector. Because of these issues, it is necessary to determine the most important factors affecting these investments. Knowing which factors most affect business

performance in energy efficiency investments gives companies an advantage over their competitors.

On the other hand, there are very few studies in the literature in which the importance weights of these criteria are determined. This situation requires a new study in which a prioritization analysis will be conducted for these performance indicators. Accordingly, the purpose of this study is to evaluate energy efficiency investments in smart manufacturing. To achieve this objective, an analysis has been conducted via double hierarchy hesitant fuzzy linguistic term-based hybrid decision-making modelling. In the first stage, experts are weighted with the help of the DHHFL-CRITIC method. In the next step, the importance of indicators/criteria is determined via the DHHFL-LOPCOW method. Finally, the investment alternatives in the energy efficiency of smart manufacturing are ranked by using the DHHFL-OPARA method. In this process, the following research questions can be identified.

(1) What are the most critical factors in improving the performance of energy efficiency investments in smart manufacturing?

(2) How can the most appropriate investment alternatives be ranked to evaluate the performance of energy efficiency investments in smart manufacturing?

(3) How do the importance levels of the criteria determined in energy efficiency investments change, and what are the main reasons for this change?

(4) What advantage does the dual-hierarchy hesitant fuzzy linguistic term-based hybrid decision-making model (DHHFL) provide in the evaluation of energy efficiency investments?

(5) How can strategic planning processes be made more effective in energy efficiency investments?

(6) How do the effects of the criteria determine energy efficiency investments in different production areas in the industrial sector change?

(7) What is the relationship between the payback period of energy efficiency investments and the determined critical factors?

These research questions triggered the curiosity of authors to review the literature on energy efficiency investment option selection, and we identified certain gaps in the extant studies, such as:

- Experts, who are crucial in the decision process, have varying relative importance (or weights) in a decision context, which is either not considered or directly assigned without any mathematical grounds, causing subjectivity/inaccuracies in the decision process.
- Also, experts exhibit certain interdependencies in their rating, which is not considered during the decision process, leading to less rationality.
- Criteria weights are calculated in extant models, but the spikes in preference distribution are not controlled leading to fluctuations in criteria importance.

- Finally, extant models rank investment options, but the computational feasibility is low because of the standard normalization process in many ranking methods.

Thus, the main motivation of this study is to increase energy efficiency in smart production and to determine which investments should be made as a priority in this process by circumventing the gaps pointed out above. Thanks to smart production technologies, new opportunities can be obtained to increase energy efficiency to a higher level. However, there is no clear view on which investment alternatives and criteria are more effective in this process. This study also contributes to determining the most effective investment strategies in terms of energy efficiency. The new decision-making model proposed in this study also has some contributions to the literature, as clarified in the next section. Specifically, the rationale behind considering these approaches is mentioned below:

- The use of the CRITIC technique in expert weighting provides a methodical calculation that reduces subjectivity in the process. This technique considers the interactions/interdependencies between the experts along with the variation in preference distribution to determine the weights (relative importance) of experts.
- Further, energy efficiency performance indicators (criteria) in smart production can affect each other. Due to this situation, objective weighting of indicators is essential. LOPCOW is extended to determine the weights, which considers the nature or type of indicators during weight determination and also handles fluctuations or spikes in the opinions from extreme cases through the logarithmic function.
- Finally, a recently developed ranking procedure called OPARA is extended to DHHFLTS for rationally ranking energy-efficient investments. The OPARA method has reduced complexity by omitting the normalization process and provides ranking by considering the nature of indicators/criteria.

These methods are integrated to form a decision framework that is used for selecting energy efficiency investment options. To help readers quickly grasp the contributions of this research, we summarize the contributions here. The challenge/gap of effectively representing rating data of decision entities (complex expressions) is resolved via mapping the linguistic expressions to integers within a square matrix form, which provides clarity to decision experts (or stakeholders) during the decision process. The challenge/gap of methodical determination of experts' weights, along with the consideration of the interdependencies of experts, is handled by DHHFL-CRITIC, which uses correlation and variance measures to circumvent the challenge. Likewise, the challenge/gap of fluctuations or spikes in preferences owing to extreme scale values is nullified through DHHFL-LOPCOW, which uses log functions to smooth spikes. Finally, the challenge/gap of computational complexity during rank determination is circumvented by DHHFL-OPARA, which eliminates the normalization procedure, which reduces the complexity during rank determination.

This study is organized further as follows. The second section focuses on the literature review. The proposed methodology is detailed in the third part. The usefulness of the developed model is testified to through an example in the fourth part. Later, the pros and cons of the model are realized in the fifth section via sensitivity and comparative analyses. In the sixth section, results and implications are discussed. Finally, the main conclusions are underlined in the final section along with the future directions for research.

2. Literature review

This section provides a review of earlier studies on energy efficiency investment, DHHFLTS, CRITIC, and LOPCOW methods, along with insights from the review.

2.1 Review of energy efficiency investment studies

One of the important factors affecting energy efficiency investments in the smart manufacturing process is idle time (Huang et al., 2024). Idle time refers to when production machines are not operating or operating at a lower capacity (Tian et al., 2024). Therefore, energy consumption can continue even if there is no active production. Furthermore, minimizing idle time contributes to reducing energy waste. In addition, it ensures the continuous operation of the production line and energy efficiency (Ma et al., 2023). Managing idle times can also reduce the need for equipment maintenance. Mansour and Abohashima (2023) examined ways to achieve energy efficiency by optimizing production processes. The research results argue that the business model that minimizes idle time in the production process contributes to energy efficiency. Abusaq et al. (2023) aimed to improve energy performance through lean and artificial intelligence approaches. It is stated that the idle time of flexographic machines is reduced by 30% with the lean approach and machine learning method.

Maintenance is another important factor affecting the efficiency of smart manufacturing (Firdaus et al., 2023). The most efficient operation of machines is possible with regular maintenance. Machines without maintenance consume more energy than usual (Ren et al., 2023). Besides this, maintenance prevents unexpected breakdowns of machines. These breakdowns cause problems in the production line and avoid energy savings (Yussuf and Asfour, 2024). Additionally, regular maintenance extends the life of the equipment (Daly et al., 2023). In this way, a more efficient and energy-efficient process can be managed in the production line. Milovanović et al. (2023) aimed to ensure energy efficiency in the production and maintenance process. It is emphasized that maintenance has a direct impact on energy efficiency. Surenther et al. (2023) aimed to maximize energy efficiency in wireless sensor networks for data transmission. It is stated that maintenance is an important part of achieving this goal.

Waste management also affects energy efficiency investments in the smart manufacturing process (Ehsanifar et al., 2023). Minimizing waste generation is possible through effective waste management. Reducing waste generation means reducing the need for energy. In addition, generating energy from waste is possible with effective waste management. This is an essential

way of ensuring energy efficiency (Durak, 2023). Furthermore, proper waste management also contributes to the reduction of carbon emissions (Liu et al., 2023). Güven et al. (2024) analyzed the cabin waste management process in the aviation industry in terms of energy efficiency and sustainability. It is argued that regenerating energy from the waste generated can contribute to energy efficiency. Litvinova et al. (2023) examined the contribution of green businesses in Russia and Central Asia to energy efficiency. It is reported that energy efficiency indicators are positively affected by waste management, especially in Kyrgyzstan.

Another important factor affecting energy efficiency investments in the smart manufacturing process is carbon emissions (Song et al., 2023). Energy efficiency in a smart manufacturing environment promotes a less environmentally damaging and sustainable production model. Therefore, it facilitates the achievement of environmental sustainability goals (Shah et al., 2024). In addition, low-emission technologies enable the optimization of the energy used. Accordingly, energy efficiency is achieved. This provides energy savings in the long run and attracts attention as an incentive for investments (Wang et al., 2023). Zhou et al. (2023) examined the relationship between energy efficiency growth and carbon emission growth rate. The results of the study conducted in Sub-Saharan African countries emphasize that carbon emissions decrease as energy efficiency increases. Xie et al. (2023) investigated the impact of carbon emission policies on energy efficiency in China. The importance of achieving energy efficiency in reaching the neutral carbon target is underlined.

As a result of the literature review, it is possible to mention some important points. Energy efficiency investments have become very important recently. Energy efficiency investments in smart manufacturing processes have critical importance in terms of reducing production costs, providing a sustainable production environment, and achieving environmental goals. However, many factors affect energy efficiency in this process. When these factors are improved, energy efficiency is inevitable. However, intervening in all these indicators at the same time causes new costs. Therefore, the improvements to be implemented should be directed towards the most important indicators. Similarly, some investment options can also be identified to improve energy efficiency. The details of these options are given in the appendix (Table A2). In this context, there is a need to identify the criteria/indicators affecting energy efficiency in the smart manufacturing process. Studies on this topic are insufficient in the literature. To overcome this deficiency, it is aimed to examine the leading indicators of energy efficiency investments in a smart manufacturing environment with a decision-making model. From this section, we provide some clarity on energy efficiency investments and emphasize the need for a decision-making framework to plan the investments rationally. In the next section, we review some studies related to DHHFLTS-based decision models.

2.2 Review of DHHFLTS-based models for decision-making

The idea of DHHFLTS was introduced in Gou et al., (2017) with an effort to improve rating experience through common communication and phrases flexibly. The two-hierarchy construct

supported the process and inspired researchers to utilize the set for decision-making. There is a primary hierarchy and a secondary hierarchy, where the secondary is the concrete support for the primary that leads to the modelling of complex linguistic expressions. Suppose the cardinality of the primary hierarchy is p and the cardinality of the secondary hierarchy is q, then the possible linguistic combination (PLC) is $p \times q$ (Krishankumar et al., 2021). As an example, if there is a primary hierarchy of cardinality 4 and a secondary hierarchy of cardinality 5, then the PLC is 20. Other linguistic models, such as 2-tuple linguistic set, HFLTS, uncertain linguistic term set, and so on, do not possess this property, which makes DHHFLTS improve expert evaluation by offering flexible, scalable, and naturally evolved expressions for rating. Gou et al., (2018) developed new distance/similarity measures to broaden the foundation of the set. Liu et al., (2018) proposed mathematical programming models with consistency/inconsistency indices under the DHHFLTS for evaluating air quality measures. Soon after, Liu et al., (2019) ranked accounting software within the university by using power operator-based aggregation under DHHFLTS. Montserrat-Adell et al., (2019) presented a flexible variant of DHHFLTS to promote group decision-making. Krishankumar et al., (2021) presented an extension of the VIKOR method to the set and applied the model for energy selection. Liu et al., (2022) evaluated talent by extending SWARA and WASPAS methods to DHHFLTS.

Recently, Zhang et al., (2023) presented a model for financial logistics firms' performance assessment by considering DHHFLTS, the ELECTRE method, and cosine similarity. Luo et al., (2024) recently expanded the three-way decision-making to DHHFLTS by presenting a superior gradus set, distance measure, and applying the model for service evaluation. Further, Luo et al., (2025) presented a sequential three-way decision concept by recalculating conditional probability and loss functions via neighborhood and regret theories and utilizing the framework for diagnosis application. From the review, we emphasize the importance of DHHFLTS as a rating information for decision-making. In the next section, the authors review studies that have extended CRITIC and LOPCOW methods to different fuzzy variants and decision applications for determining the weights (or relative importance) of decision entities.

2.3 Review of CRITIC and LOPCOW approaches

Both CRITIC and LOPCOW methods are objective weight calculation methods that have been used in decision-making studies by researchers owing to the merits these methods possess. Here, we review some studies. Ecer and Pamucar (2022) gave the inception to the LOPCOW method. Likewise, Diakoulaki et al., (1995) gave the inception for the CRITIC method.

LOPCOW method

Ecer et al., (2023) evaluated micro-mobility options for urban transport by extending LOPCOW and CoCoSo to an interval variant of fuzzy neutrosophic context. Simic et al., (2023) developed an extension to LOPCOW and ARAS in the neutrosophic context and ranked material handling technologies. Ecer et al., (2023) also extended LOPCOW and VIKOR to qRung orthopair context for drone selection to promote agriculture. Ulutas et al., (2024) assessed logistic providers for car

manufacturers by extending LOPCOW and MACONT methods to grey numbers. Rong et al., (2024) graded projects about offline programming systems of industrial robots by extending LOPCOW and ARAS to an interval version of Fermatean fuzzy data. Nisel and Nisel (2024) assessed countries based on their innovation potential by applying LOPCOW and CoCoSo methods. Performance assessment of the honorary teacher is conducted by utilizing the LOPCOW and MARCOS approaches. Likewise, organic food is selected by considering the EDAS and LOPCOW combination to support customer decisions.

CRITIC method

Chen et al., (2022) performed risk assessment of red tides through an integrated approach involving Monte Carlo simulation, TOPSIS-ASSETS, and CRITIC procedures. Zafar et al., (2021) utilized CRITIC with entropy for evaluating the blockchain systems. Green energy options are selected based on CRITIC, entropy, and TOPSIS approaches, and an experimental analysis is also considered (Lakshmi et al., 2022). Companies that heavily depend on coal-electricity integration seek to evaluate coal suppliers based on short-term data and apply the CRITIC method with improvement on the interrelationship part to understand variability of factors (Zhong et al., 2023). Low-carbon mobility systems are graded based on CRITIC, DEMATEL, and deep learning methods (Zhan et al., 2024). Wang et al. (2024) ranked food suppliers by considering Pythagorean fuzzy data and CRITIC-MARCOS combination to calculate importance of factors and ranks of suppliers. By considering the interval version of picture fuzzy for uncertainty, along with CRITIC, SWARA, and CODAS methods for assessing renewable energy systems with respect to sustainable and development aspects. Bilişik et al., (2024) presented CRITIC and TOPSIS under the interval variant of intuitionistic fuzzy data for transport mode selection. In the work done by Du et al., (2024), 23 cities in China are graded in terms of their transformation from coal resources by considering a combination of CRITIC and TOPSIS approaches. From the review, the importance of the CRITIC and LOPCOW methods for weight determination is presented. In the next section, the authors present specific insights to the readers based on the literature review.

2.4 Insights

The most important factors must be determined to increase the performance of energy efficiency investments. Investing in the wrong areas causes businesses to use their budgets inefficiently. This situation raises the problem of resource waste. Maximum efficiency can be obtained from investments by determining the critical factors. By selecting the most effective factors, decision makers can clearly see which areas should be given priority. When these issues are taken into consideration, it is understood that priority analysis should be performed for these criteria. On the other hand, the limited number of studies in the literature on this issue is determined as a significant gap. The priority analysis to be performed to eliminate this deficiency can be performed with a multi-criteria decision-making model. On the other hand, there are some criticisms in the literature regarding these models. Many models rely on expert opinions when determining the criteria weights. However, expert opinions may cause subjective analyses to be made. Moreover, the

selected criteria can directly affect the results of the model. Incorrect or missing criteria can lead to misleading decisions. Inadequate uncertainty management is one of the essential criticisms of multi-criteria decision-making models. In the real world, a lack of data can produce misleading results. In this study, we review research work from the context of application as well as methods. From the review, the following insights can be gained:

- Investment in terms of energy efficiency is a crucial area for research, specifically in the smart manufacturing context, but there are only limited studies in the literature.
- DHHFLTS is a promising set that can flexibly accept ratings from experts in a common language form.
- LOPCOW and OPARA are relatively new approaches for weight determination and ranking, and their extension to different fuzzy sets is a promising scope of research.
- Also, CRITIC is a popular and powerful method that researchers use actively in the sustainability assessment field.

To clarify the identified research gaps and provide literature support to the claim, in Table 1, research gaps are summarized from the extant models. Some features are missing in the extant models that add value to the decision process and facilitate rational decision-making.

Table 1 Research gaps in extant models aiding in energy efficiency selection

Sources	Consideration of complex linguistic expression	Calculation of experts' weights	Consideration to experts' interdependencies	Computationally feasible ranking
Taylan et al., (2016)	No	No	No	No
Hernández et al., (2018)	No	No	No	No
Zhou et al., (2019)	No	No	No	No
Wang et al., (2020)	No	No	No	No
Dincer et al., (2022)	No	No	No	No
Banadkouki (2023)	No	No	No	No
Yuksel et al., (2024)	No	No	No	No
Tushar et al., (2024)	No	No	No	No
Abolhassani et al., (2025)	No	No	No	No
Proposed	Yes	Yes	Yes	Yes

From the method's perspective, specific key contributions are:

- Mapping DHHFLTS to integer values and making the process of rating simple and elegant for experts. Following this, a straightforward/logical approach for score calculation is also presented.

- Interdependencies among experts are captured from their rating data, and the relative importance (or weights) of experts are methodically determined.
- Criteria weights are methodically calculated by nullifying the effects of extreme values or spikes in the preference distribution, sensibly normalizing the rating to eliminate the natural log of 0 situation.
- The computationally feasible ranking approach is extended to DHHFLTS, which is a recent method in the literature, and its exploration in complex decision problems with linguistic expression is a promising contribution to the literature.

These inferences motivate researchers to propose an integrated framework for analyzing energy efficiency investment alternatives that could feasibly handle the core challenges of decision-making, such as uncertainty modeling, ease of rating, reduced human intervention, and resemblance with human cognition. In the next section, the detailed step-by-step procedure for determining decision parameters such as weights of experts, criteria, and ranks of alternative investment options is discussed.

3. Methodology

In this section, we present some preliminaries of the DHHFLTS and its operations along with steps for determining the weights of experts, the weights of criteria, and the ranks of investment alternatives.

3.1 Basic concepts

Definition 1 (Herrera et al., 2008): $G = \{s_p | p = 0,1, \dots, \tau\}$ is an LTS with cardinality $\tau + 1$, s_0 as an initial element, and s_τ as a final element. Some characteristics are,

- If $d > c$, then $s_d > s_c$, where d, c can be the values from $0,1, \dots, \tau$
- Negation of $s_d = s_c$ if $c + d = \tau$, where d, c can take values from $0,1, \dots, \tau$.

Definition 2 (Rodriguez et al., 2011): G is an LTS. F is an HFLTS that is continuous and has finite a subset of elements from G and is given by,

$$F = \{g, h(g) | g \in G\} \quad (1)$$

where $h(g)$ has continuous finite elements from G, and $h(g) = \{s_p^r | r = 1,2, \dots, \#h(g), p = 0,1, \dots, \tau\}$ and $\#h(g)$ is the instance count.

Definition 3 (Gou et al., 2017): G is an LTS. $D = \{o_t^r | t = 0,1,2, \dots, \varepsilon\}$ is another LTS. The DHHFLTS is given by,

$$V = \left\{ s^r_{p<o_t^r>} | r = 1,2, \dots, \#v, p = 0,1, \dots, \tau, t = 0,1, \dots, \varepsilon \right\} \quad (2)$$

where $\#v$ is the instance count, $\tau + 1$ and $\varepsilon + 1$ are the cardinalities of primary and secondary linguistic terms.

Note 1: A special case of DHHFLTS is called the double hierarchy linguistic term set, which has one instance or, in other words, $\#v = 1$.

Note 2: Let $v_a = \left\{s^r_{p<o^r_t>} | r = 1,2,\dots,\#v, p = 0,1,\dots,\tau, t = 0,1,2,\dots,\varepsilon\right\}$ be the double hierarchy hesitant fuzzy linguistic element (DHHFLE), and collectively, they form DHHFLTS.

Note 3: In this work, $s_p | p = 1\ is\ disastrous, p = 2\ is\ useless, p = 3\ is\ bad, p = 4\ is\ dissatisfactory, p = 5\ is\ normal, p = 6\ is\ satisfactory, p = 7\ is\ good, p = 8\ is\ useful, p = 9\ is\ perfect$ and $o_t | t = 1\ is\ not\ highly, t = 2\ is\ not\ so, t = 3\ is\ not\ particularly, t = 4\ is\ somewhat, t = 5\ is\ simply, t = 6\ is\ just, t = 7\ is\ particularly, t = 8\ is\ so, t = 9\ is\ highly$

Definition 4 (Gou et al., 2017): Two DHHFLEs are v_1 and v_2 as before. Arithmetic operations are given by,

$$v_1 \otimes v_2 = X^{-1}\left(\cup_{\varsigma_1 \in X(v_1), \varsigma_2 \in X(v_2)} (\varsigma_1 \varsigma_2)\right) \quad (3)$$

$$v_1 \oplus v_2 = X^{-1}\left(\cup_{\varsigma_1 \in X(v_1), \varsigma_2 \in X(v_2)} (\varsigma_1 + \varsigma_2 - \varsigma_1 \varsigma_2)\right) \quad (4)$$

$$\alpha v_1 = X^{-1}\left(\cup_{\varsigma_1 \in X(v_1)} 1 - (1 - \varsigma_1)^{\alpha}\right)\ \alpha \geq 0 \quad (5)$$

$$v_1^{\alpha} = X^{-1}\left(\cup_{\varsigma_1 \in X(v_1)} (\varsigma_1)^{\alpha}\right)\ \alpha \geq 0 \quad (6)$$

where X and X^{-1} are functions for mapping the information.

Operations such as multiplication, addition, scalar multiplication, and power are shown in Eqs. (3)-(6).

Here, $X(z) = \frac{x+2\tau}{4\tau}$ and $X^{-1}(z) = (2z-1).(2\tau)$ is for the primary hierarchy and $X(z) = \frac{x+2\varepsilon}{4\varepsilon}$ and $X^{-1}(z) = (2z-1).(2\varepsilon)$ for the secondary hierarchy that help in arithmetic operations.

Before presenting the detailed step-by-step procedure for determining the decision parameters, we summarize the components of the methods for clarity to readers. In the proposed framework, three methods are extended. CRITIC is presented for experts' weight calculations. LOPCOW is presented for the criteria weights estimation. OPARA is extended for ranking energy investment options. In the CRITIC approach, the components include the score calculation of each matrix from experts, followed by the calculation of the Pearson correlation coefficient for each expert's data, the determination of variance values from the decision matrices provided by experts, the calculation of the information vector, and the normalization of this vector to obtain the weights of experts.

Likewise, for LOPCOW, the components include determining score values, calculating weighted scores by multiplying experts' weights, normalizing the weighted score matrix, determining the percentage value to obtain a vector, and finally, normalizing this vector to get the weights of

criteria. For OPARA ranking method, the components are determine the score matrix for each expert, aggregate the scores to obtain a single decision matrix, determine the 'range-based pairwise adjusted ratio' and it is a square matrix, further, determine the 'linearity-based pairwise adjusted ratio', which is also a square matrix, by using these two square matrices, we obtained 'aggregated pairwise adjusted ratio', which is finally normalized and averaged for obtaining the ranks of the alternative energy investment options. It must be noted that the three adjusted ratio matrices are of the same order - $a \times a$, where a is the number of alternatives. Based on these preliminaries, we present the steps for calculating the weights of experts and criteria in the next section.

3.2 Weight determination procedure

In this section, a detailed step-by-step procedure for weight calculation of experts and criteria are presented. In a decision process, experts and criteria are crucial decision entities/parameters and determination of weights or relative importance of these entities methodically, mitigates bias and inaccuracies (Kao 2010; Koksalmis and Kabak 2019).

Experts' weights are determined through the CRITIC approach. Later, the criterion weights are determined through the LOPCOW approach. These approaches are extended to DHHFLTS for determining the weights. Apart from the reduction in bias and inaccuracies, the methods also enable consideration of interactions among experts and hesitation during preference elicitation. Furthermore, the ability to handle small fluctuations or changes, and the impact of outliers through a logarithmic function, adds to the merit of the weight determination module.

Specifically, the weight module encompasses two methods, viz., DHHFL-CRITIC and DHHFL-LOPCOW, for determining the weights of experts as well as criteria. Both methods determine weights objectively and do not require elicitation of any additional information except the preferences/ratings. Some popular techniques, such as entropy, variance, or additive methods, do not exhibit such merit values. So, in this study, the authors present a detailed step-by-step procedure for calculating experts and criteria weights through these approaches.

DHHFL-CRITIC method

Step 1: Collect data from k experts to form $a \times b$ matrices. Here a alternatives are rated by b criteria. Complex expressions are modelled as DHHFLTS.

Step 2: Convert the DHHFLTS to fuzzy values by using conversion procedure described in Definition 4. Determine the score value by using Eq. (7).

$$c_{ij}^{l} = 0.50.\dot{\beta}_{ij}^{l} + 0.50.\dot{\gamma}_{ij}^{l} \tag{7}$$

where $\dot{\beta}_{ij}^{l}$ is the average primary hierarchy transformed value for the rating given by the expert l on the alternative i based on the criterion j, $\dot{\gamma}_{ij}^{l}$ is the average secondary hierarchy transformed value for the rating given by expert l on alternative i based on criterion j.

Step 3: Obtain interdependencies among experts by using Eq. (8). A $i \times i$ correlation matrix is calculated by considering input from Step 2. k such matrices are obtained.

$$P_{i\times i} = \frac{\Sigma_{j=1}^{b}\left((c_{iJ}-\dot{c_\iota})_x.(c_{iJ}-\dot{c_\iota})_y\right)}{\sqrt{\Sigma_j\left((c_J-\dot{c_\iota})_x\right)^2.\Sigma_j\left((c_{iJ}-\dot{c_\iota})_y\right)^2}} \tag{8}$$

where j is the index associated with b, $\dot{c_\iota}$ is the average score value of alternative i, x and y are any two alternatives, and $P_{i\times i}$ is the interrelationship matrix.

Step 4: Determine the information value for each expert by using Eq. (9) and by normalizing the information, weights of experts are obtained, which is presented as a vector of $1 \times k$ order.

$$e_l = \frac{\sigma_l^2.\Sigma_\phi(\Sigma_{\varphi=1}^{k}(1-\rho_{\phi\varphi}))}{\Sigma_l(\sigma_l^2.\Sigma_\phi(\Sigma_{\varphi=1}^{k}(1-\rho_{\phi\varphi})))} \tag{9}$$

where σ_l^2 is the variance value associated with the expert l and e_l is the weight of the expert l.

It must be noted that $P_{i\times i} = \left[\rho_{\phi\varphi}\right]_{a\times a}$. e_l is in the unit interval, and when the values are added, they yield one. When an expert gets a high weight value from CRITIC, it means that the particular expert provides a rating that has better capability to discriminate decision alternatives by considering a wider range of preferences in the distribution. Likewise, the considered expert has less correlation or redundancy with other experts, indicating that the data from the expert adds new information to the process rather than repetition or echoing of existing information from others. Thus, the usefulness of the method is well justified.

DHHFL-LOPCOW method

Step 1: Form k vectors of order $1 \times b$ by considering complex expressions for rating, which is later modelled as DHHFLTS.

Step 2: Apply Eq. (7) to convert the data from Step 1 to a score matrix of order $k \times b$. Determine the weighted score by multiplying expert weights with score value.

Step 3: Normalize the data from Step 2 to obtain a normalized score matrix of $k \times b$ order. Eq. (10) is applied for normalization by considering formulation from max-min operation.

$$ns_{lj} = \begin{cases} \frac{c_{max}-c_{lj}}{c_{max}-c_{min}}.(nmax-nmin)+nmin\ when\ j\ is\ benefit \\ \frac{c_{ij}-c_{min}}{c_{max}-c_{min}}.(nmax-nmin)+nmin\ when\ j\ is\ cost \end{cases} \tag{10}$$

where c_{max} is the maximum score value, c_{min} is the minimum score value, and c_{lj} is the score value obtained for a rating given by expert l on criterion j.

There are two modifications presented towards the normalization of the score. First, we introduce a variant of min-max normalization that could normalize values within a specific range, apart from the usual unit range. This step is mainly applied when we get zero as the resultant normalized value, leading to situations where the log function yields unreasonable values. In such cases, we

consider 0.1 as nmin, which sets 0 to 0.1, thereby supporting the use of the log function. Second, we believe the risk appetite nature of experts during normalization, where the focus is to identify datapoints closer to cost type and away from benefit type. The usual LOPCOW procedure normalizes values in the unit range, which is between 0 and 1, and follows risk averse nature.

Step 4: Calculate the percentage value (PV) by using the numerator of Eq. (11) and obtain the weights of the criteria by normalizing the PVs. This PV is used to neutralize the effects of extreme values and to capture small fluctuations in preferences effectively.

$$w_j = \frac{\left(ln\left(\frac{\left(\sqrt{\frac{\sum_{l=1}^{k} ns_{lj}^2}{k}} \right)}{\sigma_j} \right) \right).100}{\sum_j \left(ln\left(\frac{\left(\sqrt{\frac{\sum_{l=1}^{k} ns_{lj}^2}{k}} \right)}{\sigma_j} \right) \right).100} \tag{11}$$

where σ_j is the deviation associated with the criterion j, $ln(.)$ is natural log function, and w_j is the weight of criterion j.

Weights of experts and criteria are calculated methodically by using the steps presented above. It must be noted that expert bias impact the final rankings in the following ways: firstly, expert bias can lead to altered priority for alternatives than the actual – specific alternatives get higher or lower ranks than they actually deserve; secondly, importance of criteria might fluctuate in a non-uniform fashion due to experts' bias – causing some criteria to get more importance while the other less importance, and finally, rating from a biased expert can make ranking more sensitive, thus leading to inconsistencies in group decisions. To mitigate the adverse effects of expert bias, we use a methodical approach for calculating decision entities.

By using the steps in sub-section 3.2, the weights of experts and criteria are determined methodically.

3.3 Rank determination via DHHFL-OPARA process

Ranking is considered an essential and crucial phase of a decision-making problem. The idea is to arrange the alternatives in either an increasing or a non-increasing fashion to provide the stakeholders with clarity on the priority of each alternative. By this, the stakeholders can better plan their selection and backups in case of an emergency. Researchers have developed many ranking methods, of which the pairwise comparison-based ranking methods offer better focus and are a more human-centric or human-oriented form of decision-making (Keshavarz-Ghorabaee et al., 2024).

Further, researchers pointed out the importance of avoiding normalization in the ranking procedures (Zakeri et al., 2023; Keshavarz-Ghorabaee et al., 2024), which motivated authors to look for methods that can prevent the normalization step in the formulation. One such approach is the OPARA (Keshavarz-Ghorabaee et al., 2024) that considers pairwise ratios for rank estimation and avoids a normalization step to mitigate data/information loss. Further, the two decision parameters are utilized in the formulation of OPARA to handle better variations in the ranges of rating for different criteria and also to promote linearity during rank estimation. Further, the method considers the criteria type during rank estimation. Driven by these features, in this work, we extend the OPARA method to DHHFLTS for determining the ranks of alternatives.

A step-by-step procedure for rank determination is given below:

Step 1: Obtain k decision matrices of $a \times b$ order, with a being the alternatives and b being the criteria. Complex expressions used in daily communication are employed for rating, which adds ease and elegance for experts to express their opinions/views, and they are modelled as DHHFLTS.

Step 2: By applying Eq. (7), the score values are determined, and k score matrices of $a \times b$ order are obtained. By considering the weights of experts and the score matrix, the aggregated score matrix is obtained by using a simple weighted geometry function (Liao and Xu, 2015). c_{ij} is the aggregated score value of the alternative i over the criterion j.

Step 3: Calculate the 'range-based pairwise adjusted ratio (R)' by considering data from Step 2 and criteria weights from Eq. (11). Eq. (12) is applied to calculate R, which is a square matrix of $a \times a$ order.

$$R_{\delta\lambda} = \sum_{j\in B} w_j . \left(\frac{c_{\delta j}}{c_{\lambda j}}\right)^{\xi_j} + \sum_{j\in C} w_j . \left(\frac{c_{\lambda j}}{c_{\delta j}}\right)^{\xi_j} \quad (12)$$

where δ and λ are any two alternatives, B is benefit type, C is cost type, and ξ_j is a parameter to manage fluctuations of ranges in criteria.

Further, Eq. (13) is applied determine ξ_j values.

$$\xi_j = \begin{cases} \frac{\kappa . max_j(c_{ij}) + min_j(c_{ij})}{(\kappa+1) . max_j(c_{ij})} & if \ \frac{max_j(c_{ij}) - min_j(c_{ij})}{max_j(c_{ij}) + min_j(c_{ij})} > \theta \\ 1 & otherwise \end{cases} \quad (13)$$

where θ and κ are adjustment parameters that takes values as 0.80 and 5, respectively.

It must be noted that these values are adapted from Keshavarz-Ghorabaee et al., (2024).

Step 4: Calculate 'linearity-based pairwise adjusted ratio (L)' by using Eq. (14). Like R, L is also a square matrix of order $a \times a$. Here, we adjust the linearity parameter ϑ to simplify decision process.

$$L_{\delta\lambda} = \sum_{j\in B} w_j . \left(\frac{c_{\delta j}}{c_{\lambda j}}\right)^{\vartheta_j} + \sum_{j\in C} w_j . \left(\frac{c_{\lambda j}}{c_{\delta j}}\right)^{\vartheta_j} \quad (14)$$

where δ and λ are any two alternatives and ϑ_j is the linearity parameter of criterion j.

Step 5: Form 'aggregated pairwise adjusted ratio (A)' by using Eq. (15). Results from Eq. (12) and Eq. (14) are combined in a linear fashion to obtain A.

$$A_{\delta\lambda} = q . R_{\delta\lambda} + (1 - q) . L_{\delta\lambda} \quad (15)$$

where q can take values in the unit interval.

Step 6: The final ranking is obtained by arranging the values from Eq. (16) in the descending (or non-increasing) order.

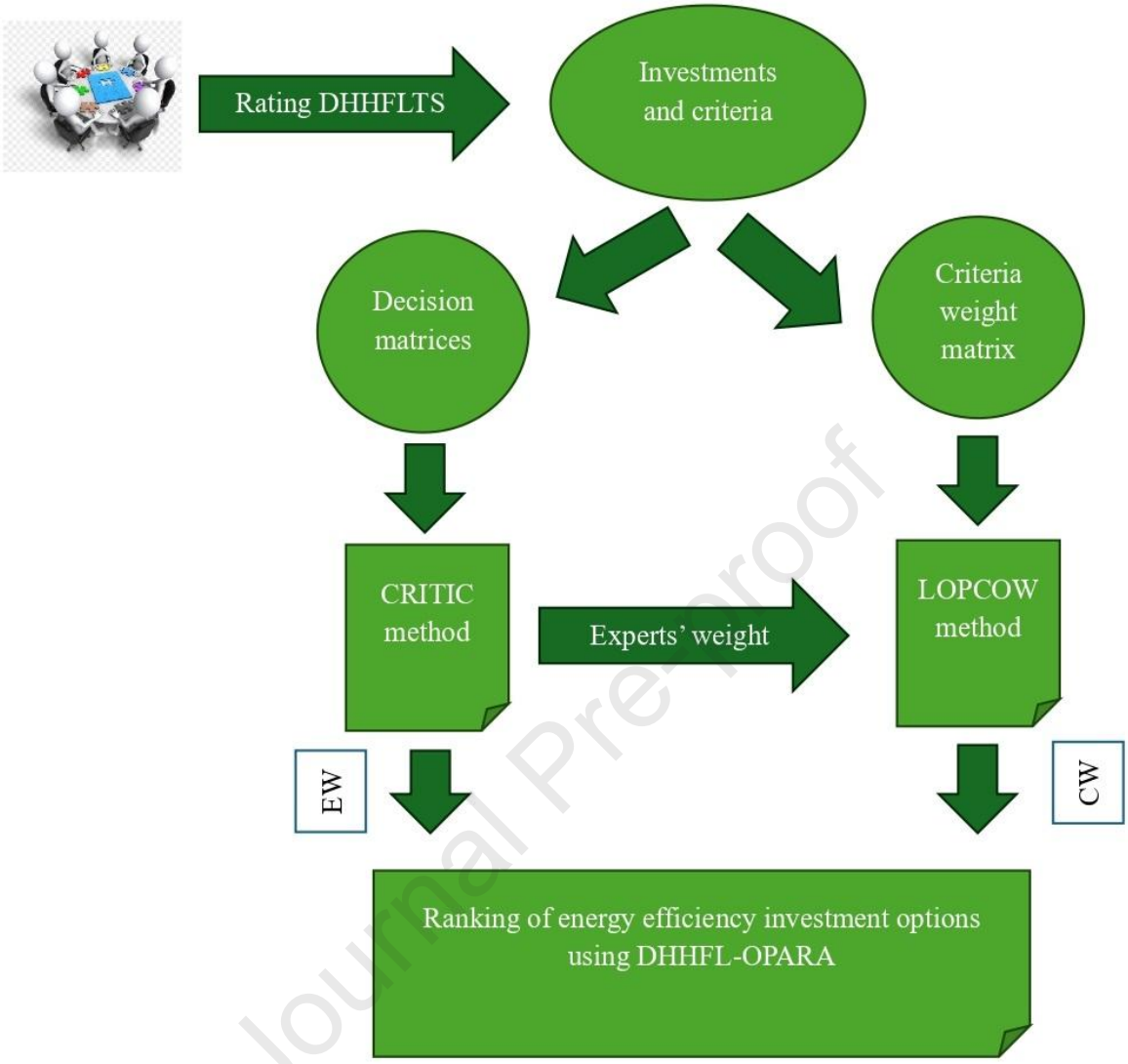
$$A_i = \frac{1}{a}\sum_{\lambda=1}^{a}\left(\frac{A_{\delta\lambda}}{\sum_{\delta} A_{\delta\lambda}}\right) \quad (16)$$

where a is the number of alternatives and A_i is the final rank value of alternative i.

It must be noted that Eq. (16) yields a vector of $1 \times a$ order, and the ordering of alternatives is done by arranging the A_i in descending order, which in other words denotes higher ranks to higher A_i values. The DHHFL-OPARA method offers a ranking of alternatives by taking into consideration the linearity aspect and minimizing or neutralizing the effect of different ranges over the criteria set. Further, the ranking procedure facilitates rank estimation for alternatives by considering a holistic effect/play of all criteria considered for the study rather than a specific instance.

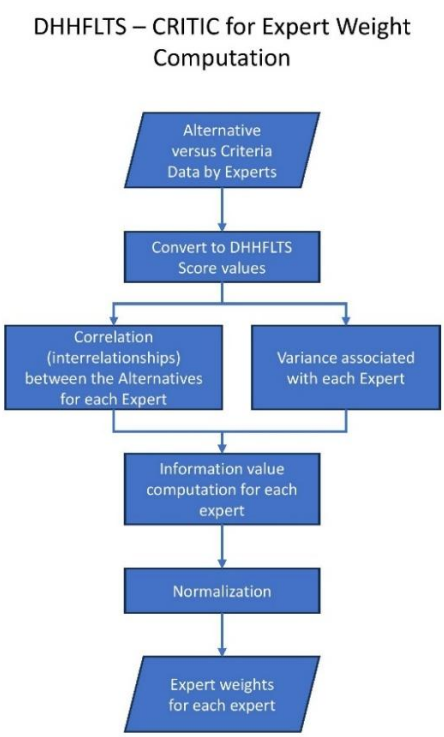
From the working model presented in Fig. 1, it is clear that the proposed model reduces human intervention by methodically calculating values for decision parameters. DHHFLTS is considered for modelling the complex linguistic expressions from experts. Later, the weights of both criteria and experts are methodically determined. Weights of experts, specifically, are utilized for both criteria weight estimation and rank determination. Criteria weights, along with ratings from experts, are used for ranking energy efficiency investment options. DHHFL-CRITIC method is presented for determining the weights of experts. Likewise, the DHHFL-LOPCOW method is proposed for calculating the weights of criteria. Finally, the DHHFL-OPARA method is proposed for ranking the energy efficiency investment options. From this sub-section, we obtain the ranks of different alternatives, and the practicality of the developed framework is demonstrated through an example in the next section.

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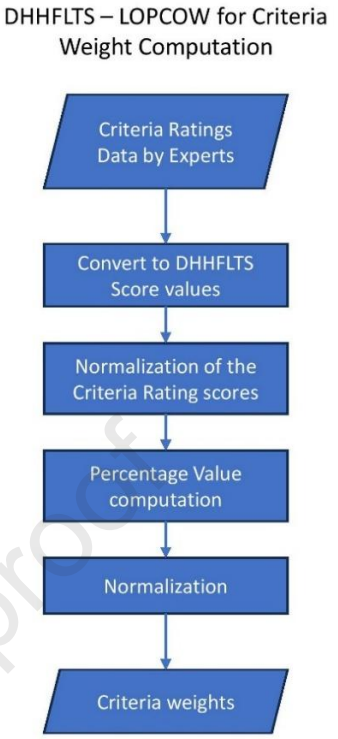


(a)

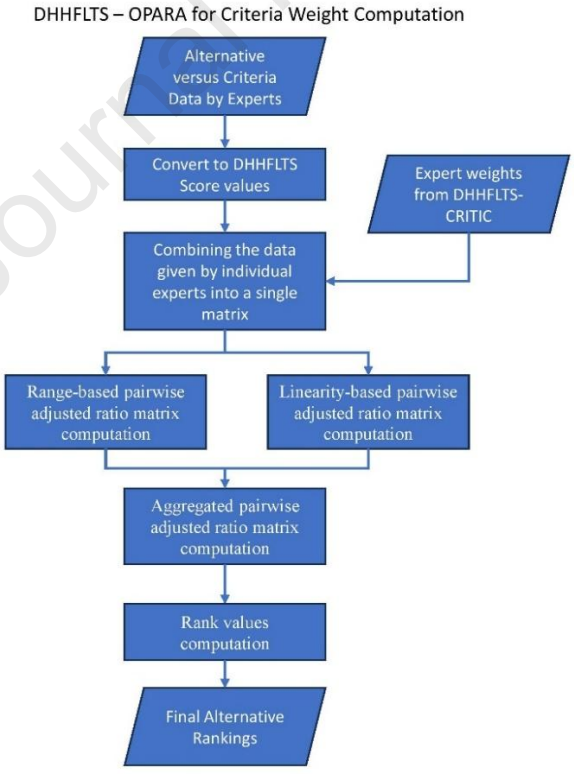
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(b1)



(b2)



(b3)

Fig. 1 (a) Working model of DHHFL-integrated framework for energy efficiency investment (b1) Workflow of DHHFLTS-CRITIC (b2) Workflow of DHHFLTS-LOPCOW (b3) Workflow of DHHFLTS-OPARA

Fig. 1 depicts the working of the developed framework. k matrices of order $a \times b$ are obtained as input – decision matrices from k experts. Likewise, one matrix of order $k \times b$ is obtained as input for determining the weights of the criteria. DHHFL-CRITIC is applied to k matrices of $a \times b$ for determining the weights of experts. Similarly, the DHHFL-LOPCOW method is applied on the $k \times b$ matrix for determining the weights of the criteria. The weights of experts are also fed as input during the criteria weight assessment. By considering the weights of experts $(1 \times k)$ and criteria $(1 \times b)$ along with $a \times b$ matrices from k experts, DHHFL-OPARA is applied for determining the ranks of alternative energy efficiency investment options. Finally, a rank vector of $1 \times a$ is obtained.

Before understanding the usefulness of the framework, it is essential to note that the framework is proposed with an intention to reduce human intervention in determining values for decision parameters so that bias and inaccuracies are mitigated. For this reason, key entities like weights of experts, weights of criteria, and ranks of alternatives are methodically determined. Due to this, the computational complexity of the framework increases and a detailed study on the complexity is planned for the future. Currently, from the logical standpoint, by considering different methods for calculating different entities, it is clear that the complexity is high, but the framework can be effectively used in the real-world by gaining some training with the framework – as the proposed model can provide logical decision to stakeholders based on the input by reducing human intervention in determining parameter values, which might incur inaccuracies and bias.

For brevity, we present the working of the proposed framework. Initially, k matrices are considered of order $a \times b$. By using the expert weight calculation procedure in Section 3.2, a vector of $1 \times k$ is obtained. Likewise, a matrix of $k \times b$ is obtained, which is given as input to the criteria weight calculation procedure in Section 3.2 along with the $1 \times k$ expert weight vector to get a weight vector of $1 \times b$. Finally, k matrices of $a \times b$ are given as input to Section 3.3 along with the expert weight vector $1 \times k$ and the criteria weight vector $1 \times b$ for determining the ranks of alternative energy efficiency investment options – a $1 \times a$ vector. The idea is also pictorially represented in Fig. 1(a). From the developed framework, it is noted that the decision entity values are consistently used by other entities, showcasing a 'closed loop' structure, which signifies effective formulation and adds to the novelty of the study. For criteria weights, experts' weights are utilized, and for ranking, both criteria weights and experts' weights are utilized, giving a connected framework for decision-making, which is lacking in extant constructs.

4. Case example

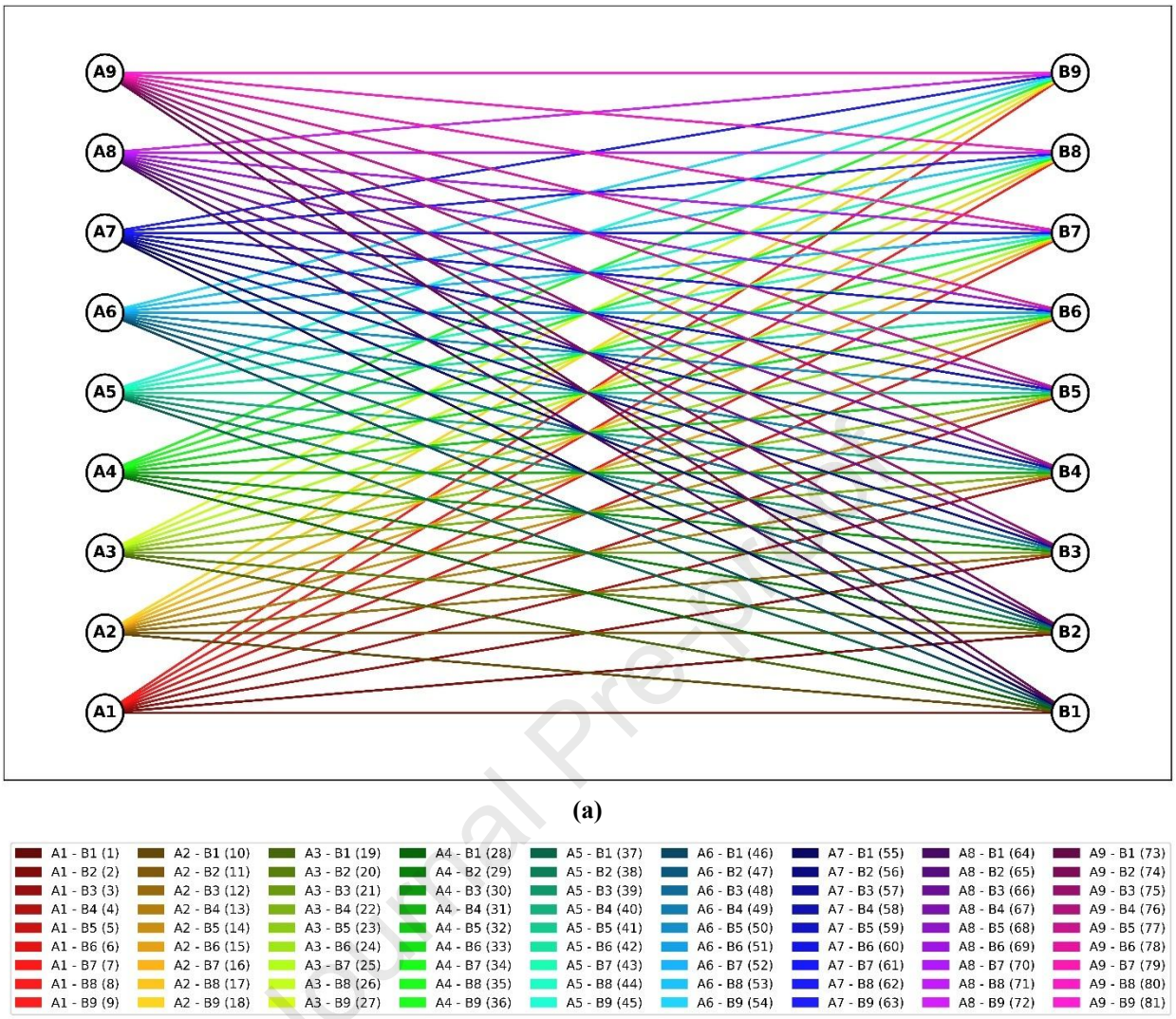
This section demonstrates the practical use of the proposed framework by presenting an energy efficiency investment selection problem.

4.1 Background

In this study, it is aimed to evaluate energy efficiency investments in smart manufacturing with DHHFL term-based hybrid decision-making modelling. First, experts considered in this study are

weighed by DHHFL-CRITIC method. After that, selected criteria are weighed by DHHFL-LOPCOW method. Finally, investment alternatives in the energy efficiency of smart manufacturing are ranked by DHHFL-OPARA. Criteria set for assessing energy efficiency in smart manufacturing are defined as carbon emissions (C1), idle time (C2), recycling energy (C3), maintenance (C4), failures (C5), and waste management (C6). High carbon emissions may cause governments to impose strict regulations. These practices may lead the industry and energy sectors to make investments that increase energy efficiency. The idle tile in the production process causes energy waste. This situation leads to a significant decrease in energy efficiency. Recycling energy is an important strategy that increases energy efficiency. In this process, used or waste energy sources can be re-evaluated. Regular and correct maintenance optimizes energy consumption and ensures that systems operate more efficiently. More energy is consumed in machines that do not undergo regular maintenance. Failures can have significant negative effects on energy efficiency. Unexpected failures in systems lead to energy losses. Reducing waste optimizes energy consumption and prevents waste of resources. Less material waste prevents unnecessary energy use in production. These six criteria are identified as the most important based on a review of the existing literature on energy efficiency in smart manufacturing. Prior studies in the field of smart manufacturing emphasized the significance of these criteria in optimizing production processes and reducing energy consumption.

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(a)

(b)

Fig. 2 Visual representation of the mapping of integer values to corresponding DHHFL terms – (a) is the bipartite graph representing the mapping and (b) is the legend

On the other side, an alternative set for ranking the investment alternatives in the energy efficiency of smart manufacturing is defined as renewable energy integration (A1), energy monitoring systems (A2), lean manufacturing systems (A3), green building design (A4), and sustainable supply chain (A5). Renewable energy integration is the process of efficiently incorporating different renewable energy sources into existing energy systems. This integration reduces

dependency on fossil fuels. Energy monitoring systems are systems that monitor the consumption of energy sources in real-time. The primary purpose of these systems is to optimize energy consumption. Lean production systems detect and reduce unnecessary energy consumption. This contributes significantly to energy savings. Green building design is a building design process carried out to increase environmental sustainability. Sustainable supply chain is the understanding of optimizing and directing supply chain processes by taking environmental, social, and economic factors into account.

Apart from the discussion related to the application that is being focused, it is also essential to understand the construct of the DHHFLTS that we adopted in this study. We consider the DHHFLTS as two hierarchies with nine terms each and as result, a matrix with 81 combinations in the form of 9×9 is possible.

Table 2 Mapping of DHHFLTS into integer

Map	o_1	o_2	o_3	o_4	o_5	o_6	o_7	o_8	o_9
s_1	1	2	3	4	5	6	7	8	9
s_2	10	11	12	13	14	15	16	17	18
s_3	19	20	21	22	23	24	25	26	27
s_4	28	29	30	31	32	33	34	35	36
s_5	37	38	39	40	41	42	43	44	45
s_6	46	47	48	49	50	51	52	53	54
s_7	55	56	57	58	59	60	61	62	63
s_8	64	65	66	67	68	69	70	71	72
s_9	73	74	75	76	77	78	79	80	81

Note: Elements row wise denote primary hierarchy and elements column wise denote secondary hierarchy.

In Table 2, the DHHFLTS are mapped to an integer, and $\left\{s^1_{1<o^1_1>}\right\}$ is denoted as '1', and which means 'not highly disastrous'. Likewise, $\left\{s^1_{9<o^1_9>}\right\}$ is denoted as '81', and it means 'perfectly high'. To further clarify the mapping of integers to complex linguistic expressions, it must be noted that there are nine terms in the primary hierarchy and nine terms in the secondary hierarchy, which can yield 81 combinations. The two extreme cases are stated above, but suppose an integer value of '4' is taken – it means that in the primary hierarchy, we consider s_1, and in the secondary hierarchy, we consider o_4, and the meaning of the integer '4' is 'somewhat disastrous'. Likewise, if we choose the integer value as '23', then from the primary hierarchy it is s_3 and in the secondary hierarchy it is o_5 with the meaning of '23' as 'simply bad'. In the same way, the rest of the data is represented. Before presenting the calculation procedure, it is essential to understand certain assumptions by collecting data from experts and defining the criteria weights. Firstly, the dataset must be complete, and missing or unavailable values are not allowed. Secondly, the experts are allowed to use only integer values between the range 1 and 81 (refer to Table 2) as rating information. Finally, during criteria weight calculation, normalization is done in a homogeneous fashion by considering min/max within the specific criteria type/nature – benefit or cost types. To support further clarity on the mapping, we present Fig. 2(a) and Fig. 2(b), which are bipartite graphs with color codes and legends clarifying the mapping of integers to linguistic terms. Based on the background

provided in this subsection, a detailed step-by-step procedure for calculating the decision parameters and finally obtaining a suitable investment option is provided in the following subsection.

4.2 Calculation procedure

For ease of representation, we denote experts as Expert 1, Expert 2, and Expert 3. Alternative energy efficiency investments (EEI) are denoted as A1, A2, A3, A4, and A5. Criteria are denoted as C1, C2, C3, C4, C5, and C6. C5 and C6 are cost types, and rest are benefit types.

Step 1: Three experts give their rating on five alternative EEI based on six criteria.

Table 3 Rating of EEI by experts

Expert 1	A1: Renewable Energy Integration	A2: Energy Monitoring Systems	A3: Lean Manufacturing Systems	A4: Green Building Design	A5: Sustainable Supply Chain
C1: Carbon Emission Control	63	45	37	54	68
C2: Load Time	45	54	37	54	45
C3: Recycling Energy	72	68	63	72	68
C4: Maintenance	54	45	41	54	54
C5: Failures	37	41	37	45	37
C6: Waste Generation	68	63	54	68	72
Expert 2	A1: Renewable Energy Integration	A2: Energy Monitoring Systems	A3: Lean Manufacturing Systems	A4: Green Building Design	A5: Sustainable Supply Chain
C1: Carbon Emission Control	81	77	67	81	79
C2: Load Time	56	60	52	60	56
C3: Recycling Energy	77	79	72	77	79
C4: Maintenance	60	56	52	60	60
C5: Failures	52	56	41	56	52
C6: Waste Generation	79	77	67	79	79
Expert 3	A1: Renewable Energy Integration	A2: Energy Monitoring Systems	A3: Lean Manufacturing Systems	A4: Green Building Design	A5: Sustainable Supply Chain
C1: Carbon Emission Control	74	67	63	74	67
C2: Load Time	50	67	68	67	50
C3: Recycling Energy	67	64	63	67	67

C4: Maintenance	49	54	50	54	49
C5: Failures	41	52	41	52	41
C6: Waste Generation	64	67	63	64	67

Table 3 provides the rating for EEI based on different criteria. The mapping shown in Table 2 is utilized for rating and the semantic of the integer values can be clarified from the discussion made in Section 4.1.

Step 2: Three experts rate the six criteria. Table 4 is used for representing criteria rating data as given by the experts.

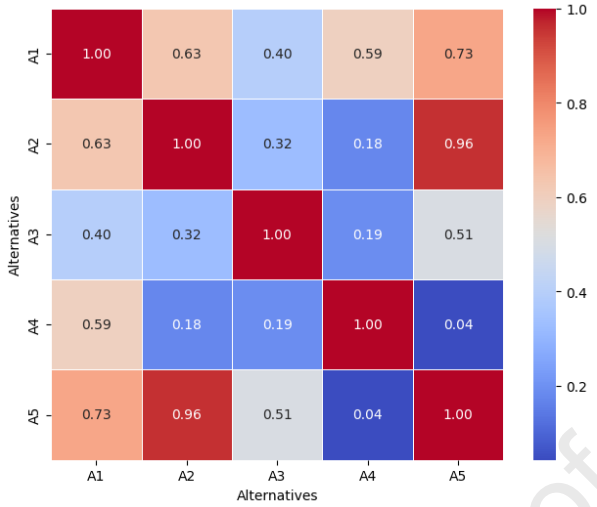
Table 4 Criteria rating by experts

Criteria	Expert 1	Expert 2	Expert 3
C1: Carbon Emission Control	63	81	74
C2: Load Time	45	56	50
C3: Recycling Energy	72	77	67
C4: Maintenance	54	60	49
C5: Failures	37	52	41
C6: Waste Generation	68	79	64

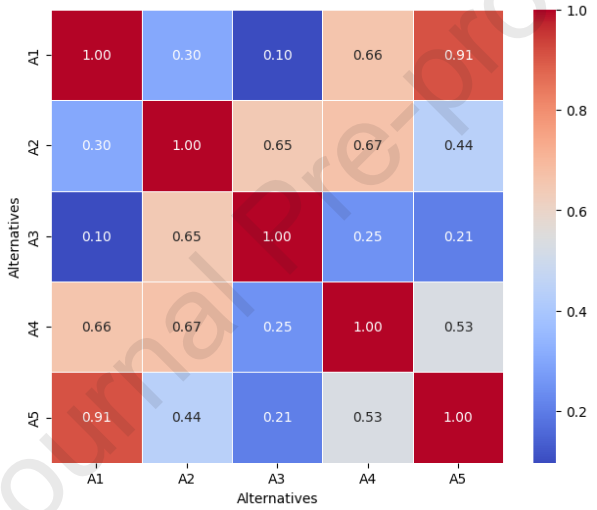
Step 3: Determine the weights of experts and criteria by considering data from Step 1 and Step 2.

Based on Eq. (7), the score value is determined. As a result, three score matrices of 5×6 are obtained with five EEIs rated based on six criteria. From Eq. (8), correlation is determined and a vector of 1×3 is obtained. Variance values are also determined based on the preferences from experts and by applying Eq. (9), the information is determined, which is further normalized to obtain weights of experts. Fig. 3 shows the interrelationship (absolute correlation) among the alternative ratings given by the experts. Experts' weights are calculated as 0.57, 0.26, and 0.17, respectively.

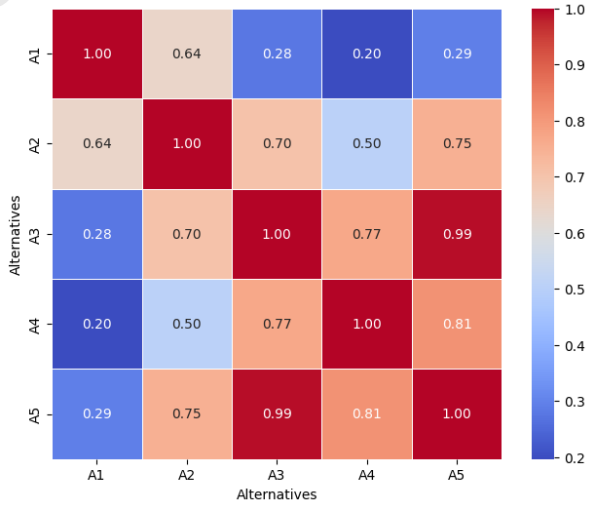
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(a)



(b)



(c)

Fig. 3 Interrelationship value of the alternatives (a) is for expert 1, (b) is for expert 2, and (c) is for expert 3

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From the correlation of experts, it is noted that Expert 1 is having high uniqueness in terms of rating when compared Expert 2 and Expert 3, followed by Expert 2 and then it is Expert 3 with net coefficient of uniqueness as 10.51, 8.55, and 8.12, respectively (obtained after adding coefficients of (1 – correlation) value matrix). This indicates that the rating from Expert 1 is fairly unique compared to other experts, inferring that there is some value addition from the data rather than mere repetition. Further, from the variance value, we understand the distribution. Typically, an expert with less correlation to other experts' ratings and higher variance gains higher importance, indicating that the specific expert is unique as well as shows less response bias. Hence, correlation values play a crucial role in determining the relative importance (or weights) of experts in the decision process, as stakeholders generally prefer new directions or perspectives from an expert's data. Likewise, we apply Eq. (7) to the data in Table 5 and obtain the score that forms a matrix of order 3×6. Eq. (10) is used to obtain the normalized data, which is further fed to Eq. (11) for determining the percentage value that is, in turn, normalized to obtain the weights of the criteria. A vector of 1×6 is obtained. The normalized matrix obtained from Eq. (10) is shown in Fig. 4, and weights are calculated as 0.150, 0.292, 0.078, 0.327, 0.122, and 0.031, respectively.

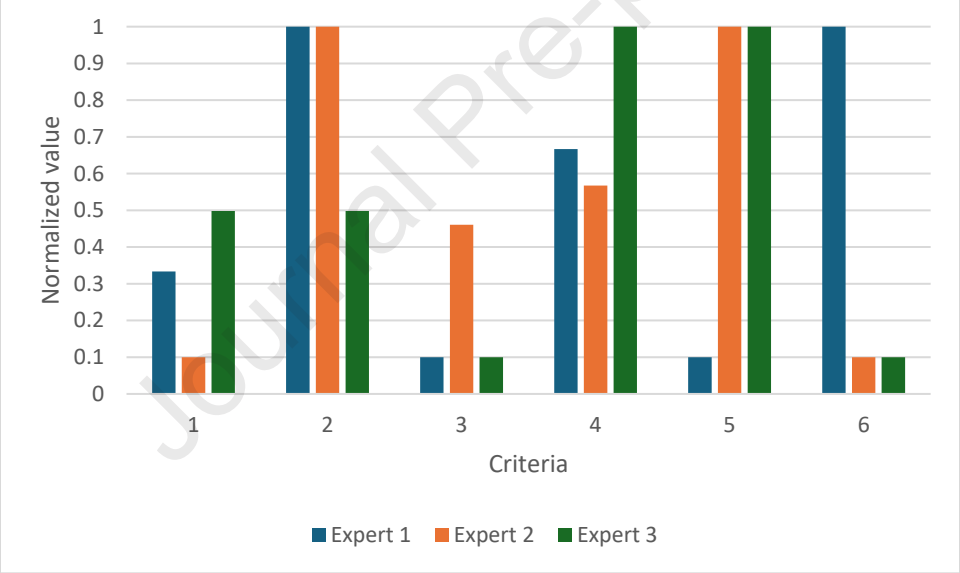


Fig. 4 Normalized values for LOPCOW method

Step 4: Ranks of EEI are calculated by considering data from Step 1 and weights from Step 3.

Table 5 Pairwise adjusted ratios for OPARA

$R_{\delta\lambda}$	A1	A2	A3	A4	A5
A1	1	1.010419	1.058808	0.996601	1.010742
A2	0.990698	1	1.049294	0.986477	1.001017
A3	0.94644	0.956662	1	0.944031	0.956397
A4	1.004857	1.014476	1.064712	1	1.01553
A5	0.989697	0.999693	1.047641	0.98623	1
$L_{\delta\lambda}$	A1	A2	A3	A4	A5
A1	1	1.021965	1.123419	0.99472	1.021940

A2	0.982498	1	1.105038	0.97389	1.002745
A3	0.897628	0.918834	1	0.896218	0.916572
A4	1.011108	1.029913	1.138844	1	1.032767
A5	0.979812	1.000087	1.099599	0.97427	1

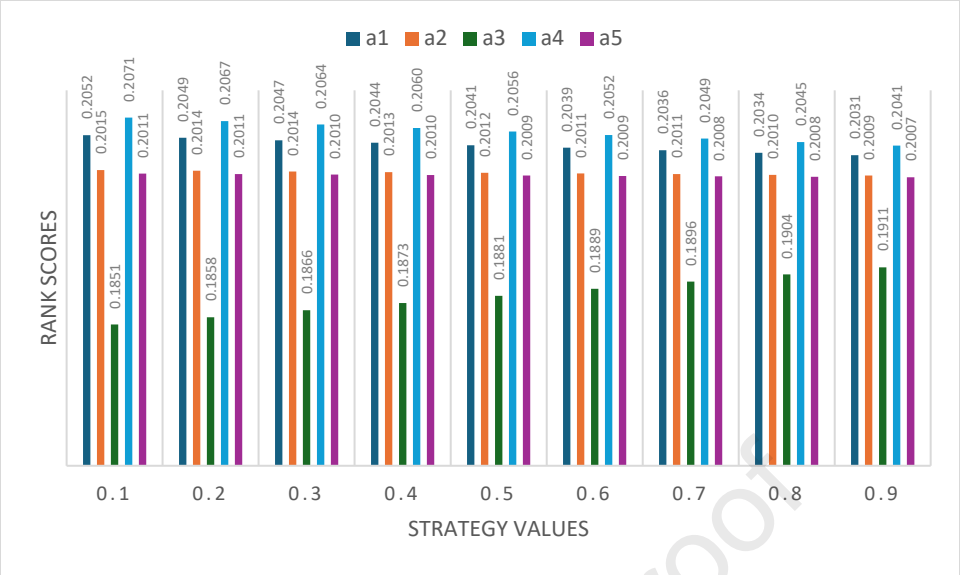
By considering the rating from experts, the weights of experts, and the criteria, we calculate the range-based pairwise adjusted ratio $R_{\delta\lambda}$ by applying Eq. (12). A matrix of 5×5 order is obtained. Likewise, by applying Eq. (14), the linearity-based pairwise adjusted ratio $L_{\delta\lambda}$ is determined, and a matrix of 5×5 order is obtained. These two matrices are shown in Table 5. Using Eq. (15)-(16), the rank values are determined for EEIs that help in ordering the alternative EEIs. From Eq. (16), the rank values are obtained as A1 = 0.20415, A2 = 0.201214, A3 = 0.188099, A4 = 0.205607, and A5 = 0.200929, and the ordering is given by A4 > A1 > A2 > A5 > A3. The practicality of the proposed model is demonstrated in this subsection and in the next section, we discuss the efficacy of the proposed framework.

5. Sensitivity analysis and comparison

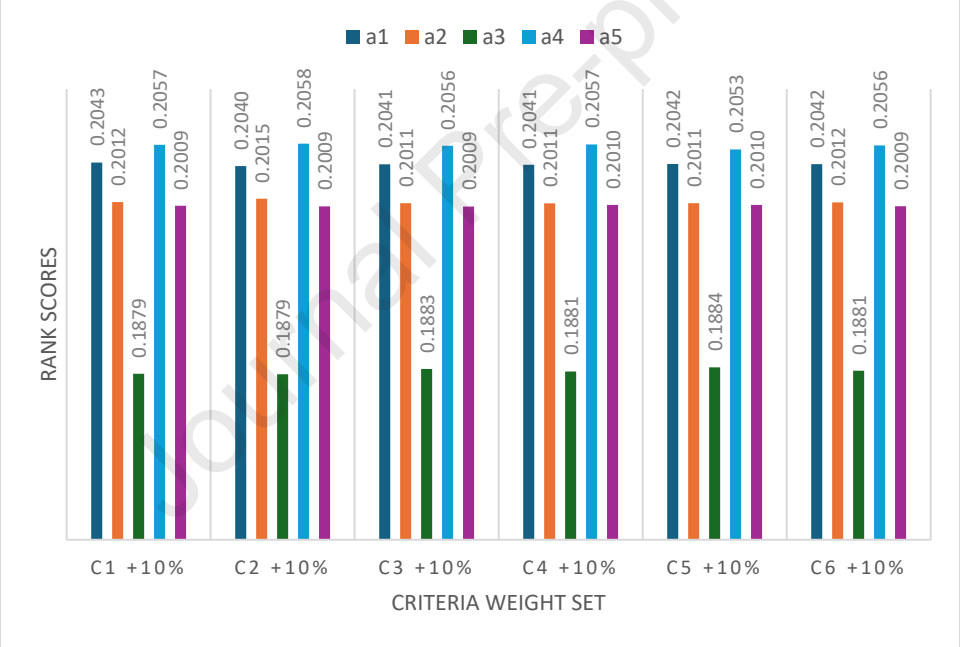
The results of an MCDM analysis can vary significantly when different expert groups are consulted or when the criterion weights are altered. Each expert group may bring distinct perspectives, knowledge domains, or biases based on their background, which can influence the evaluation of criteria and alternatives. For example, industry professionals might prioritize cost-effectiveness, while academic experts may focus more on innovation or sustainability. Additionally, since MCDM techniques often rely on subjective weight assignments, even small changes in these weights can shift the ranking of alternatives. Therefore, it is essential to conduct sensitivity analysis or robustness checks to assess how stable the final rankings are across different weight scenarios. In this section, we perform a sensitivity analysis by varying strategy values (intra-sensitivity) and criteria weights (inter-sensitivity). We also compare the developed framework with extant models to realize the merits of the proposed model.

5.1 Inter and intra sensitivity

In this section, the efficacy of the proposed framework is examined. We present two forms of sensitivity analysis to showcase the robustness of the proposed framework comprehensively. Two forms are the sensitivity analysis of strategy values by considering the weights of criteria determined via Section 3.2 and data from Table 3. Another form is a sensitivity analysis of the weights of the criteria that we obtained and used in Section 4. The former form is referred to as intra-sensitivity, and the latter form is referred to as inter-sensitivity. In intra-sensitivity, we alter strategy values stepwise in the unit range by considering values between 0 and 1. Likewise, in inter-sensitivity, we consider the weights of criteria by adopting $\pm 10\%$ weight fluctuations.

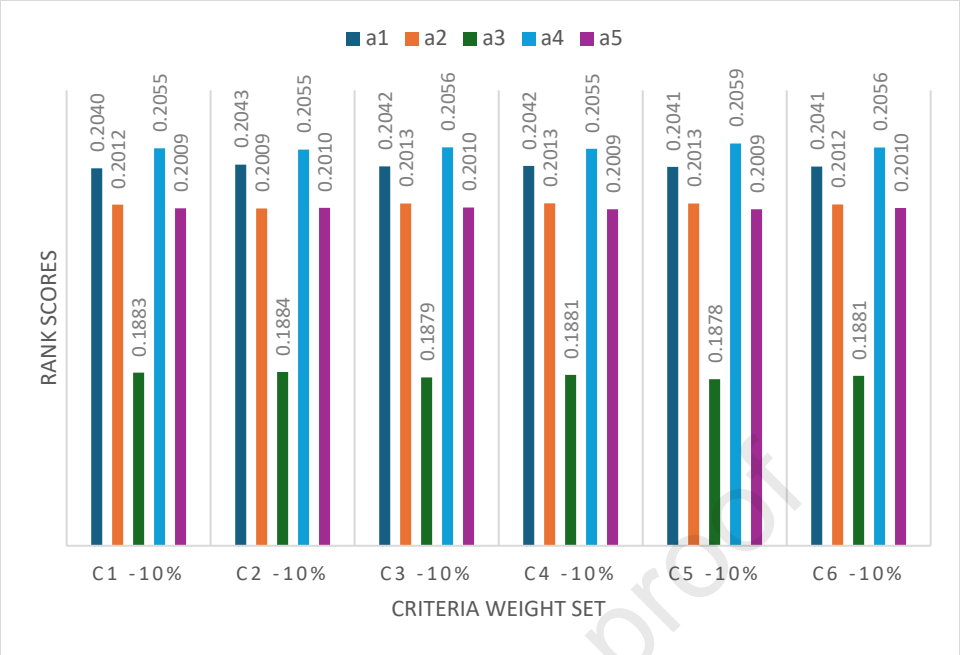


(a)



(b)

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(c)

Fig. 5 Sensitivity analysis (a) is strategy value alteration, (b) is +10% criteria weight alteration, and (c) is -10% criteria weight alteration

As a result, in the former form, we will have nine instances or episodes with values being 0.10, 0.20, 0.30…, 0.90. Similarly, in inter-analysis, we will have weights of criteria altered by $+10\%$ and -10% and so, we will have six new sets of weights of $+10\%$ and six new sets of weights for -10%. These values will be fed to the ranking module along with the rating data to calculate rank values and the ordering of EEIs. Based on these values, graphs are plotted in Fig. 5, and a discussion is made from the results. The stability in the rank order provides decision experts with certain benefits, which adds support to their decisions. Specifically, there is reduced sensitivity to bias that allows the framework to mitigate personal bias and stakeholder disagreements to the determined relative importance of decision entities, thereby yielding objective decisions. Furthermore, communication with stakeholders becomes easy with a consistent rank order despite alterations of weights of decision entities, as experts can confidently narrate the decisions to stakeholders, and a win-win situation can be created. Also, situations of excessive deliberation with stakeholders and repeated analyses can be mitigated, which in turn saves resources for the organization.

From Fig. 5(a), Fig. 5(b), and Fig. 5(c), it is clear that the proposed framework is robust, and the ordering remains unchanged even after adequate alterations are made to strategy values and weights of criteria. Obviously, the rank values show change, but the rank order is intact (A4 > A2 > A1 > A5 > A3), indicating that the proposed DHHFLTS-based framework with CRITIC-LOPCOW-OPARA methods is robust against the influence of parameter alterations. Robustness can be noticed in both the intra and inter-sensitivity forms. It must be noted that Fig. 5(a) focuses on the intra-sensitivity analysis where the strategy values are altered from 0.10 to 0.90 to visualize

their effect on the rank values and rank order. Likewise, in the inter-sensitivity analysis category, we alter the criteria weights by +10% and -10%. This percentage is chosen based on the general practice in the literature with regard to sensitivity analysis. In the future, other step sizes such as 5%, 15%, 20%, and so on may also be considered to understand the influence of weight alterations on the rank order. Based on Fig. 5(a), Fig. 5(b), and Fig. 5(c), it is observed that the rank orders remain intact despite changes in rank values – there is a relative change in the rank value across alternatives that is leading to the intactness of the rank order. From Fig. 5, it is clear that rank orders do not change, which gives a sense of confidence to the decision experts that their choice is not an artifact of assigning weights subjectively. Further, the sensitivity analysis offers traceability in the context of a 'what-if' situation, where experts look for situations – what will happen if the relative importance (or weights) of say 'criterion c1' is increased/decreased by a certain percentage – which provides decision experts clarity on the significance of criteria and its role in the decision process. In this sub-section, we presented intra and inter-sensitivity analysis and realized the efficacy of the model with respect to alterations of strategy values and criteria weights. In the next sub-section, we compare the proposed model with other models that are involved in EEI selection to showcase the merits of the proposed model.

5.2 Comparison

Decision-making models can be preferred to identify the most critical items. Similarly, some scholars created decision models that have focused on solving the energy efficiency investment selection problem. Kshanh and Tanaka (2024) tried to focus on the evaluation of energy efficiency projects towards sustainable industrial energy management. To achieve this objective, fuzzy analytical hierarchy process (AHP) is taken into consideration. Similar to this study, Li et al. (2023) and Marenco-Porto et al. (2023) also conducted a study on green finance investment decisions to reach energy efficiency. However, the main criticism of this study is that the interactions between the variables are not considered. In addition to this, Talal et al. (2024) and Sundaram et al. (2024) also aimed to find the best strategy alternatives to obtain energy efficiency with the help of Vlse Kriterijumska Optimizacija I Kompromisno Resenje (VIKOR) technique. These models are criticized because the results are dependent on the normalization phase/procedure.

Table 6 Comparison of different models related to energy efficiency context

Factors	Proposed	Kshanh and Tanaka (2024)	Li et al., (2023)	Marenco-Porto et al., (2023)	Talal et al., (2024)	Sundaram et al., (2024)
Complex linguistic expressions	Allowed	Not allowed	Not allowed	Not allowed	Not allowed	Not allowed
Interrelationship among experts	Considered	Not considered	Not considered	Not considered	Not considered	Not considered
Experts' weights	Calculated	Not calculated	Not calculated	Not calculated	Not calculated	Not calculated
Variation in opinions on criteria	Handled	Not handled	Not handled	Not handled	Not handled	Not handled
Complexity	High	Low	Moderate	Low	Low	Moderate

Ranking without normalization	Allowed	Not allowed	Not allowed	Not allowed	Not allowed	Not allowed

In Table 6, the comparison of different models that focus on energy efficiency is presented. From the factors, it is clear that the proposed framework performs better compared to the existing models, but has a high computational complexity owing to the methodical determination of different decision parameters. But the present-day hardware facilities enable or support the implementation of such models, and as a result, rational and less biased decisions can be made for the better growth of business. Some key takeaways on the reasons for the proposed framework to outperform other models are:

- The proposed framework considers DHHFLTS, which can effectively accept complex linguistic expressions that decision experts use in their daily communication. Extant models cannot accept such expressions in the rating of decision entities.
- Decision experts are crucial in a decision process, and it is obvious that the relative importance of the experts is not equal. Methodical determination of the weights reduces subjectivity/bias as argued by Koksalmis and Kabak (2019). Extant models do not follow this, and to manage the issue, the proposed framework determines experts' weights by DHHFL-CRITIC, which considers interdependencies among experts and variability in the preferences to determine the weights.
- Similarly, criterion weights are crucial in a decision problem. Extant models cannot nullify the effects of spikes from extreme values – DHHFL-LOPCOW can effectively nullify the effect by smoothening the spikes using the log function, which in turn yields weights that are distributed smoothly across decision entities. Also, the weights of experts are included as input in the criteria weight calculation procedure, which is lacking in extant models. When we compare the results of the criteria weights with the entropy measure and the variance measure, we observe that the discrimination ability of DHHFL-LOPCOW is superior compared to other popular methods – variability is approximately ten times better compared to extant methods.
- Finally, by extending OPARA, we reduce complexity in rank determination by omitting the normalization procedure in the ranking process.

Some trade-offs that must be considered are: firstly, the computational complexity of the proposed model is high compared to the counterparts; secondly, experts (or in general stakeholders) need certain level training to effectively use the model for rational decision-making; and finally, the model cannot accommodate missing values in the rating and some a priori choices on decision entities. The key findings from the sensitivity analysis and comparison are:

- From the sensitivity analysis, it is inferred that rank order remains unchanged - A4 > A2 > A1 > A5 > A3 with 'Green building design' as highly preferred investment option even after performing alterations of strategy values (Fig. 5a) and criteria weights (Fig. 5b and Fig. 5c).

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- Compared to the extant models, the proposed model allows flexible rating of entities by considering daily communication expressions, which is lacking in other models. Also, decision parameters are methodically determined rather than direct assignment, which reduces bias and inaccuracies. Besides, the consideration of interdependencies among experts, nullifying effects of extreme values or spikes in distribution during criteria weight calculation, and ranking options with computational feasibility are unique aspects of the proposed framework from this sub-section, the merit points of the proposed model is clarified with respect to comparison with other models. In the next section, we present the discussion on the results and implication to stakeholders.

6. Discussion and implications

Before discussing the results and the implications, it is better to note that the proposed decision framework is developed using Python and Microsoft Excel for calculating the decision parameter such as experts' weights, criteria weights, and ranks of alternative energy efficiency investments along with the visual representation of certain results via bar graphs. Some limitations of the practical implementation are: data must be entered manually in the worksheets for determining the values of the decision parameters; stakeholders need certain level of training to understand the mathematical functioning of the framework – so that the yielded results make sense to the stakeholders; and at present there is no graphical user interface (GUI), but the process is in the pipeline so that stakeholders can use the GUI for feeding the data and from button clicks, they can infer results for the decision parameters. With regard to the computational complexity, we will do a comprehensive analysis in the future, but for now, we can infer that the proposed framework is computationally complex since key decision parameters are methodically determined and data/rating conversion consumes a considerable amount of time/resources. We developed the framework on the Windows 11 operating system with an Intel Core i7 processor, 16 GB RAM, and a 500 GB hard drive.

Some key novelty of the proposed framework and its impact are provided below:

- Weights of experts are methodically obtained – this aspect is lacking in extant models of EEI selection. Such determination supports reduced bias and subjectivity in the decision process enabling rational decision-making.
- Weights of experts are included in both criteria weight calculation procedure as well as ranking procedure – this aspect is also lacking in extant models of EEI selection. Besides, the DHHFL-LOPCOW enables nullifying spikes or extreme values of preference distribution during weight calculation and distributes weights smoothly among entities by maintaining better discrimination of the entities, which is lacking in other methods, such as entropy or variance measures.
- Ranking of EEI is performed with comparatively less computational complexity by omitting normalization procedure in the rank algorithm.

The results of the analysis show that the most important criterion/indicator is maintenance. Regular maintenance ensures that the production line runs efficiently. It also prevents possible malfunctions in the production line. Good maintenance is necessary for the machines to last longer. Preventing energy waste, such as overheating or low performance, is possible by providing effective maintenance. Amin et al. (2024) stated that providing effective maintenance improves air conditioning performance. Es-sakali et al. (2024) emphasized that downtime and energy costs can be better managed through systematic and effective maintenance. Idle time is found to be the second most important criterion as a result of the analysis. To maximize energy efficiency, idle times need to be minimized. Reducing idle times can also ensure continuity in the production line, thus increasing productivity. In addition, high idle times negatively affect the performance of the machines. Carmona et al. (2023) stated that idle time should be considered in the efficiency measurement of autorickshaws. Jelti and Saadani (2024) noted that managing idle time is crucial for achieving energy efficiency.

Green building design (A4), Renewable Energy Integration (A1), and Energy monitoring system (A2) are identified as the top three investment options that promote energy efficiency within the smart manufacturing sector. Construction accounts for major pollution and focuses on sustainable construction with the help of utilizing green materials and green design strategies, reducing pollution and facilitating energy efficiency (Alawneh et al., 2018; Shrestha 2016). From this, we understand that the proposed model yielded a ranking or priority to investment options in line with the literature. Further, integration of renewable energy adds value to smart manufacturing by significantly contributing to the carbon footprint reduction and promoting a sense of green energy in the manufacturing process. Integration of renewable energy substantially reduces pollution of the environment and supports in combating climate change, which is a pressing problem in the present era. Also, focusing on energy monitoring systems is essential for facilitating energy efficiency within smart manufacturing, and studies such as (Akhtar et al., 2020; Lee and Cheng, 2016; Iris and Lam 2019) emphasize the importance of energy monitoring systems in effectively managing energy. Thus, the present study stands in line with the literature and infers that investment in these options can promote energy efficiency within the smart manufacturing sector. The understanding of the top two criteria and top three investment alternatives creates a better scope for planning and strategizing energy efficiency within the smart manufacturing division.

The proposed model can be applied to sectors such as manufacturing, renewable energy, and smart grid systems. Reducing waste is a very critical issue for the effectiveness of the manufacturing process. Similarly, renewable energy projects consist of very complex processes. Hence, to provide effectiveness in these systems, this proposed model can generate appropriate solutions. In addition to them, smart grids can also help to achieve optimization in the production process. On the other hand, energy monitoring systems play a crucial role in improving long-term energy efficiency by providing real-time data on energy consumption patterns. Industry 5.0 focuses on the human-centric and sustainable integration of advanced technologies. In this process, artificial intelligence applications can be taken into consideration. This proposed model maintains a balance between

technological progress and human-centered design. This situation helps to align with Industry 5.0's sustainability goals.

The research gap identified in this study is the lack of integrated approaches that address both operational inefficiencies and environmental impacts in energy systems. The results of this proposed model contribute to bridging this gap by providing insights into how these factors can be integrated. Another critical research gap in the literature related to this subject is the deficiency in the definition of the most critical factors. In this study, it is identified that idle time reduction is the most significant factor in improving operational efficiency. Hence, this prioritization analysis helps to satisfy this missing gap in the literature. On the other hand, this study demonstrates the importance of idle time, maintenance, waste management, and carbon emissions. Thus, this study provides a comprehensive approach to improving energy system efficiency. The results of this proposed model have a guiding role for the decision-makers. They provide a roadmap for prioritizing investments in energy-efficient technologies and policies. This situation makes a positive contribution to reaching the Sustainable Development Goals. Policymakers can also benefit from the results to implement effective energy policies. Owing to this situation, it can be much easier to encourage investments in the most efficient technologies. Some implications from the study are:

- A ready-to-use system is presented with flexibility to stakeholders for sharing their opinions through a common language or day-to-day communication.
- Human intervention is mitigated by incorporating methodical determination of decision parameters, thereby reducing bias and inaccuracies in the decision process.
- The system can be used by smart manufacturers to plan their strategies for achieving energy efficiency targets, and investors can also plan the options that would better facilitate energy efficiency and aid the sustainable growth of businesses.
- When the focus globally is to transition from Industry 4.0 to Industry 5.0, the incorporation of energy-efficient strategies would expedite the transition, and sustainability promotes it.
- Stakeholders must be trained with the developed system in order to better gain the advantage of the system and make informed decisions that can be supported by data as well as a mathematical construct, which otherwise would not be possible.
- Finally, the developed model considers the pain points of stakeholders during the decision process and attempts to circumvent such challenges by promoting flexibility in rating, supporting methodical estimation of parameters, and serving as a supplementary module for stakeholders in making rational business decisions.

In this section, the authors discuss the results and implications, which facilitate a better understanding of the work for stakeholders. In the next section, we provide the concluding remarks and future research directions.

7. Conclusion

In this study, it is aimed to evaluate energy efficiency investments in smart manufacturing with double hierarchy hesitant fuzzy linguistic term-based hybrid decision-making modeling. First, experts' weights are determined by the DHHFL-CRITIC method. Later, selected criteria are weighted through the DHHFL-LOPCOW procedure. After that, investment alternatives in the energy efficiency of smart manufacturing are ranked with the DHHFL-OPARA technique. It is identified that maintenance and idle time are the most essential criteria for assessing energy efficiency in smart manufacturing. Green building design and energy monitoring systems are the most important investment alternatives in the energy efficiency of smart manufacturing.

Maintenance is a critical factor in terms of ensuring energy efficiency in smart production. In this context, regular maintenance of machines, equipment, and digital systems is necessary. With the help of this issue, the risk of equipment failure decreases. Preventing such failures increases energy efficiency in smart production facilities. Regular maintenance also ensures that equipment operates at optimum energy efficiency. In this way, it is possible to reduce energy consumption during the equipment usage process. Maintenance activities in smart production facilities ensure that production processes operate uninterruptedly. This allows energy efficiency to be increased. Various policy recommendations can be developed to increase the effectiveness of maintenance activities and ensure energy efficiency in smart production. In this context, incentive programs can be offered to businesses as a priority. This situation also contributes significantly to reducing the costs of projects. Establishing maintenance standards also supports the increase in the performance of this process. Establishing standards allows all businesses to achieve a certain quality in their maintenance processes.

The findings of this study have important implications for both theory and practice. In the theoretical sense, a new model is proposed to contribute to the literature. Thanks to the new model, reliable results can be obtained. In practical terms, a set of criteria affecting energy efficiency in smart manufacturing processes is defined. In addition, the most optimal strategies affecting energy efficiency in these processes are identified. The analysis results with the new model show that the most influential criteria are maintenance and idle time, along with the green building design and energy monitoring system being the key options for investments to support energy efficiency with smart manufacturing. The main motivation of this study is that there is no consensus about the criteria and alternatives to increase energy efficiency in smart production. The new decision-making model proposed in this study also has some contributions to the literature. The use of the CRITIC technique considers the correlation analysis between the experts. Similarly, the LOPCOW determines the importance of the criteria by nullifying hesitation, and OPARA yields ranks with less computational overhead. These novelties support the increase in the reliability of the analysis results.

The main limitation of this study is that the evaluations of all experts are done objectively. Thus, in future studies, the subjective weights of these people can be computed along with consideration

of a priori information. Further, we plan to explore the effects of different biases and the computational complexity of the proposed framework. Plans are also made to extend the framework to the probabilistic variant of the double hierarchy. Also, other energy-related problems, such as material evaluation, site selection, adoption barrier prioritization, and so on can be planned. Plans are also made to explore the computational complexity and scope of scalability of the proposed framework. Also, we plan to validate the developed framework by exploring its usefulness in real-world case studies or industry implementation. Finally, a larger perspective of decisions can be expanded by integrating concepts of recommender systems, multimedia data analysis with machine learning, and AI/metaheuristic-driven decisions. The study limits energy efficiency investments to smart production only. However, alternative application areas and industries related to energy efficiency should also be evaluated. In future studies, different sectors can be examined. With the help of this situation, the applicability of the model can be tested in a broader framework. Another limitation of the study is that it only considers the short-term effects of energy efficiency investments. On the other hand, long-term effects can also be critical in this process. In future studies, it may be useful to develop a model that examines the long-term economic and environmental effects of investments. The model developed in this work can be further validated with real-life use cases and/or industry in the future. The model proposed in this study can also be applied to different sectors. For example, this model can be taken into consideration for green building design and optimizing automotive production processes. Similarly, this model can be useful for ensuring energy efficiency in the healthcare sector. The model can offer priority strategies that can reduce energy consumption in hospitals.

CRediT authorship contribution statement

Raghunathan Krishankumar: Conceptualization, Formal analysis, Methodology, Software, Writing – original draft. **Hasan Dinçer:** Conceptualization, Data curation, Formal analysis, Review, Writing – original draft. **Serhat Yüksel:** Conceptualization, Data curation, Formal analysis, Review, Writing – original draft. **Yaşar Gökalp:** Conceptualization, Data curation, Formal analysis, Review, Writing – original draft. **KS Ravichandran:** Methodology, Investigation, Visualization, Supervision, Writing - original draft. **Jurgita Antucheviciene:** Investigation, Supervision, Validation, Writing – review and editing.

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

Data will be made available on request.

Appendix

Table A1: Abbreviations

Abbreviations	Expansions
LTS	Linguistic term set
HFLTS	Hesitant fuzzy linguistic term set
DHHFLTS	Double hierarchy hesitant fuzzy linguistic term set
DHHFLE	Double hierarchy hesitant fuzzy linguistic element
DHHFL	Double hierarchy hesitant fuzzy linguistic
CRITIC	Criteria importance through inter-criteria correlation
LOPCOW	Logarithmic percentage change-driven objective weighting
OPARA	Objective pairwise adjusted ratio analysis
VIKOR	VIseKriterijumska Optimizacija I Kompromisno Resenje
SWARA	Stepwise weight assessment ratio analysis
WASPAS	Weighted aggregated sum product assessment
ELECTRE	ÉLimination Et Choix Traduisant la REalité
CoCoSo	Combined compromise solution
MACONT	Mixed aggregation by comprehensive normalization technique
ARAS	Additive ratio assessment
MARCOS	Measurement of alternatives and ranking according to compromise solution
TOPSIS	Technique for order of preference by similarity to ideal solution
DEMATEL	Decision making trial and evaluation laboratory
CODAS	Combinative distance-based assessment
EDAS	Evaluation based on distance from average solution
AHP	Analytical hierarchy process

Table A2: Investment Options

Investment Option	The Impact on Energy Efficiency
Solar Panel Installation	Energy loss during solar energy production is relatively lower than other similar ones. This situation contributes to increased energy efficiency.
Wind Power Projects	Wind energy does not consume any fuel. This helps reduce losses in energy production.
Energy Storage Systems	Storage of electricity produced but not consumed instantly is critical for the development of renewable energy projects. With the help of this issue, grid losses are reduced and overall system efficiency is increased.
Smart Grid Infrastructure	Thanks to smart meters and sensors, energy losses on the grid are detected and minimized.

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Highlights

- Double hierarchy set is utilized for energy efficiency investment option selection.
- Both criteria and experts' weights are calculated methodically.
- Double hierarchy OPARA is presented for ranking investments.
- Green building design is the most viable investment option.
- Maintenance is a key criteria for investment selection.

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Declaration of interests

☒ 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.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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