Reducing energy consumption in industrial plants: An Integrated Multi-Criteria Decision-Making Framework with Similarity Aggregation Method

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Abstract: The reduction of energy consumption in manufacturing industries has become a primary focus, driven by increased environmental awareness and the introduction of European Directives. Adopting energy-saving solutions can not only reduce environmental impact but also enhance production performance. A prevalent strategy for achieving higher energy efficiency involves the replacement of outdated technologies within production plants. This approach is widely adopted across various industrial sectors; however, selecting the most appropriate technology is a complex task due to the vast array of solutions available in the market. Multi-Criteria Decision-Making (MCDM) methods can be employed to address this challenge, but the choice of a suitable MCDM tool is crucial, as different tools may yield varying results. Additionally, MCDM approaches typically necessitate expert elicitation, which often entails integration with Fuzzy Set Theory (FST) to manage subjectivity and uncertainty arising from expert judgments. It is essential to appropriately aggregate differing expert opinions, considering both the importance of each expert and the consensus among them. This paper proposes an integrated MCDM framework that combines a robust approach for aggregating expert opinions. We achieve this by combining the fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and fuzzy VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) methods, offering increased flexibility for users. Simultaneously, the improved Similarity Aggregation Method (SAM) is employed to aggregate the opinions of various experts, taking into account the degree of consensus. The developed framework is demonstrated through a case study of a cement plant, and it can be utilized to identify the most suitable technology for a given enterprise.

Keywords: Energy efficiency; Multi-Criteria Decision-Making; Aggregation of expert opinions; TOPSIS; VIKOR

I. INTRODUCTION

Reducing energy consumption in manufacturing industries has progressively become more important. The former trend is related to the growth of environmental awareness and the introduction of new regulations [1], such as European Directives. In this context, the introduction of new technologies plays a pivotal role [2], indeed, it can contribute to both reducing the environmental impact and improving the performance of a manufacturing plant. As a matter of fact, the replacement of old equipment with newer and more efficient ones is one of the most common strategies adopted in different industrial sectors such as the foundry [3] and the cement industry [4]. However, the market offers a wide variety of technological alternatives and the best energy-saving solution is strongly related to the priorities of each firm [5]. Accordingly, identifying the technology towards which directing efforts and investments could be regarded as a difficult task.

To deal with the complexity of decision-making related to sustainability evaluations, Multi-Criteria Decision-Making (MCDM) methods have become quite popular, being deemed as appropriate thanks to their flexibility [6]. Indeed, MCDM approaches facilitate the decision makers in comparing different alternatives with respect to different criteria of analysis [7]. Moreover, MCDM methodologies could exploit as input both quantitative and qualitative data. Considering the latter, experts or different decision makers could be involved in the analysis to express their opinions on a given topic (e.g., the importance of a criterion). Since expert opinions come with uncertainty and subjectivity, MDCD is often integrated with Fuzzy Set Theory (FST), providing more realistic, sensitive, and concrete results [8]. Moreover, experts could provide different or even conflicting opinions, leading to the requirement of aggregating them. Considering fuzzy MCDM, the aggregation of expert opinions is often treated with the simple average, the weighted average, or the minimum and maximum functions. The weighted average could include the importance of each expert, however, the agreement among experts is disregarded by all the former approaches. On the other hand, the Similarity

Aggregation Method (SAM) can also consider the expert agreement, but its adoption in MCDM context is still scarce.

In the context of MCDM methods, several different approaches can be found. Examples include Analytic Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), Preference Ranking Organization Method for Enrichment Evaluations (PROMEETHEE), and ELimination Et Choix Traduisant la REalité trois (ELECTRE III). Therefore, choosing the proper MCDM approach is a complex task [9], and the adoption of different methods could lead to different results [10].

Based on the previous considerations, this paper aims to propose an integration between an improved version of SAM and two fuzzy MCDM methods (i.e., TOPSIS and VIKOR) for selecting the most suitable energy-saving solution. The improved SAM allows considering the consensus among different experts, while the adoption of both TOPSIS and VIKOR would provide the decision makers higher flexibility.

The remainder of this paper is organised as follows; Section II presents the literature review on various MCDM approaches and aggregation methods, while Section III summarises the considered approaches. In Section IV the framework is described, while in Section V, the application of the framework to a case study is illustrated. Finally, Section VI contains the discussion, while Section VII reports the conclusions.

II. LITERATURE REVIEW

Literature offers a wide variety of MCDM methods, each of which may come with a specific set of advantages and disadvantages [11]. For instance, AHP is a simple process thanks to pairwise comparisons. However, it could be characterised by a high number of pairwise comparisons in case of large-scale problems [12]. ELECTRE allows to handle ill-structured data and add new criteria at any step of the analysis, but it is a complex [13] and time-consuming [14] process, and it provides a partial ranking of alternatives [15]. PROMETHEE presents similar advantages to ELECTRE with a smaller computational effort, but it is unable to provide a perfect ranking of the alternatives [15]. On the other hand, TOPSIS is a simple process, but it is unable to take into account the interrelationship of attributes [13]. Finally, VIKOR can determine the compromise solution out of a list of alternatives [16], which is also sometimes seen as a disadvantage [17]. Based on the previous considerations, TOPSIS was chosen for its easiness of application and its computational efficiency [18], along with being one of the most popular MCDM methods [15]. On the other hand, VIKOR was chosen thanks to its ability to identify a compromise solution. Moreover, both are able to identify a ranking of the alternatives.

Regarding the adopted methods to aggregate expert opinions in fuzzy TOPSIS, there are two main approaches, both of which are unable to consider experts' agreement [19]: i) average value and ii) minimum and maximum functions. This consideration could be extended also to other MCDM methods. To face the former challenge, quite recent papers integrated SAM with fuzzy TOPSIS to consider the consensus among experts [19], [20]. However, as stated by Ziemba et al. [19], it could be interesting to incorporate SAM with other MCDM approaches (e.g., VIKOR). Moreover, SAM cannot deal with the weight of experts when considering the agreement. Based on the previous considerations, an improved SAM developed by Guo et al. [21] is integrated with TOPSIS and VIKOR.

Thus, in this work, an integration of two popular MCDM methods and the improved SAM is proposed. First, the improved SAM is adopted to aggregate expert opinions. Next, fuzzy TOPSIS and fuzzy VIKOR are applied in sequence to provide a ranking of solutions.

III. MATERIAL AND METHODS

An overview of the main approaches adopted to conduct this study is provided in the following subsections.

A. *Fuzzy Set Theory and Similarity Aggregation Method*

A trapezoidal fuzzy number can be expressed as a quadruplet of numbers through the following notation $\tilde{A} = (a_1, a_2, a_3, a_4)$. Let $\tilde{A} = (a_1, a_2, a_3, a_4)$ and $\tilde{B} = (b_1, b_2, b_3, b_4)$ be two trapezoidal fuzzy numbers arising from the judgments of two experts, the improved SAM developed by Guo et al. [21] requires estimating the Similarity Degree (SD) through Eq. 1.

$$SD(\tilde{A}, \tilde{B}) = 1 - \frac{1}{4}\sum_{i=1}^{4}|a_i - b_i| \quad (1)$$

The SD should be computed for each couple of experts involved in the analysis and for each provided opinion. Next, given an expert E_i, its Weighted Absolute Agreement (WAA) is computed according to Eq. 2.

$$WAA(E_i) = \frac{\sum_{j=1, j\neq i}^{n} WE(E_j) SD(\tilde{A}_i, \tilde{A}_j)}{\sum_{j=1, j\neq i}^{n} WE(E_j)} \quad (2)$$

where n is the number of experts and $WE(E_j)$ is the weight associated with the j-th expert. The former weight is usually based on different factors such as educational level, age, position, and service time. Subsequently, for each expert, the Relative Agreement (RA) and the Consensus Coefficient (CC) are obtained as shown in Eq. 3 and Eq. 4, respectively.

$$RA(E_i) = \frac{WAA(E_i)}{\sum_{j=1}^{n} WAA(E_j)} \quad (3)$$

$$CC(E_i) = \beta W(E_i) + (1 - \beta) RA(E_i) \quad (4)$$

where β is a user-defined parameter called relaxation factor, bounded between 0 and 1 included. Finally, the aggregated fuzzy number ($\check{A}_{ag}$) is calculated through Eq. 5.

$$\tilde{A}_{ag} = \sum_{i=1\oplus}^{n} CC(E_i) \times \tilde{A}_i = (a_{ag1}, a_{ag2}, a_{ag3}, a_{ag4}) \quad (5)$$

The method presented in this paragraph can be extended to Triangular Fuzzy Numbers (TFNs) given that a triangular fuzzy number can be reconducted to a trapezoidal characterised by $a_2 = a_3$.

B. *Fuzzy TOPSIS*

Given a set of c criteria $C = \{c_j | j = 1 \dots c\}$ and a set of M alternatives $A = \{A_i | i = 1 \dots M\}$, the fuzzy TOPSIS requires a set of experts to associate with each criterion a weight, while assigning to each alternative a score for each criterion. Let $\widetilde{W}_j$ be the weight associated with the j-th criterion, while $\tilde{X}_{ij} = (l_{ij}, m_{ij}, r_{ij})$ is the TFN identifying the rate of the i-th alternative with respect to the j-th criterion. Both $\widetilde{W}_j$ and $\tilde{X}_{ij}$ are TFNs obtained after the aggregation of expert opinions. Accordingly, a vector of criterion weights ($\widetilde{W}$) and a decision matrix (D) could be built based on Eq. 6 and Eq. 7 [22].

$$\widetilde{W} = \{\widetilde{W}_j | j = 1 \dots c\} \quad (6)$$

$$D = \begin{bmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{1c} \\ \vdots & \ddots & \vdots \\ \tilde{x}_{M1} & \cdots & \tilde{x}_{Mc} \end{bmatrix} \quad (7)$$

Next, a normalized decision matrix is developed through Eq. 8., where $\tilde{n}_{ij}$ represent the normalized score of the i-th alternative with respect to the j-th criterion.

$$\begin{cases} \tilde{n}_{ij} = \left(\frac{l_{ij}}{r_j^*}, \frac{m_{ij}}{r_j^*}, \frac{r_{ij}}{r_j^*}\right) & \forall j \,\epsilon\, benefit\ criteria \\ \tilde{n}_{ij} = \left(\frac{l_j^-}{r_{ij}}, \frac{l_j^-}{m_{ij}}, \frac{l_j^-}{l_{ij}}\right) & \forall j \,\epsilon\, cost\ criteria \end{cases} \quad (8)$$

where $r_j^* = \max_i r_{ij}$ $\forall j \,\epsilon\, benefit\ criteria$, while $l_j^- = \min_i l_{ij}$ $\forall j \,\epsilon\, cost\ criteria$. Subsequently, based on the vectors of criteria weight, the weighted normalized decision matrix is computed, following Eq. 9.

$$\tilde{v}_{ij} = \tilde{n}_{ij} \otimes \widetilde{W}_j \quad i = 1 \dots M; j = 1 \dots c \quad (9)$$

where $\tilde{v}_{ij}$ is the weighted normalized score of the i-th alternative with respect to the j-th criterion. Based on the results arising from the previous step, the Fuzzy Positive Ideal Solution (FPIS) and the Fuzzy Negative Ideal Solution (FNIS) are estimated as shown in Eq. 10 and Eq. 11, respectively.

$$FPIS = \{\tilde{v}_j^* | j = 1 \dots c\} \quad (10)$$

$$FPIN = \{\tilde{v}_j^- | j = 1 \dots c\} \quad (11)$$

where $\tilde{v}_j^* = \max_i \tilde{v}_{ij}$, while $\tilde{v}_j^- = \min_i \tilde{v}_{ij}$ [23]. For each alternative, the distances from the FPIS and FPIN are computed according to Eq. 12 and Eq. 13, respectively.

$$d_i^* = \sum_{j=1}^{c} d(\tilde{v}_{ij}, \tilde{v}_j^*) \quad (12)$$

$$d_i^- = \sum_{j=1}^{c} d(\tilde{v}_{ij}, \tilde{v}_j^-) \quad (13)$$

In Eq. 12-13 the distance between two TFNs is obtained as depicted in Eq. 14.

$$d(\tilde{A}, \tilde{B}) = \sqrt{\frac{1}{3} * [(l_A - l_B)^2 + (m_A - m_B)^2 + (r_A - r_B)^2]} \quad (14)$$

Finally, the Closeness Coefficient (C_{coeff}) is estimated as shown in Eq. 15. C_{coeff} represents the goodness of a given alternative. Specifically, good alternatives should be close to $FPIS$ and far from $FPIN$. The higher C_{coeff}, the better the alternative is for TOPSIS. Thus, it is possible to rank the alternatives based on C_{coeff}.

$$C_{coeff} = \frac{d_i^-}{d_i^- + d_i^+} \quad (15)$$

C. *Fuzzy VIKOR*

As for fuzzy TOPSIS, the fuzzy VIKOR starts from a set of criteria (C) and a set of alternatives (A). Fuzzy VIKOR also requires a group of experts, who express their opinions on the importance of each criterion and the rate of each alternative with respect to each criterion. First, the ideal solution denoted as $\tilde{X}_j^* = (l_j^* m_j^* r_j^*)$ and nadir solution identified as $\tilde{X}_j^- = (l_j^- m_j^- r_j^-)$ are estimated for each criterion based on Eq. 16 and 17, respectively [24].

$$\begin{cases} \tilde{X}_j^* = \max_i \tilde{X}_{ij} & \forall j\ benefit\ criteria \\ \tilde{X}_j^* = \min_i \tilde{X}_{ij} & \forall j\ cost\ criteria \end{cases} \quad (16)$$

$$\begin{cases} \tilde{X}_j^- = \min_i \tilde{X}_{ij} & \forall j\ benefit\ criteria \\ \tilde{X}_j^- = \max_i \tilde{X}_{ij} & \forall j\ cost\ criteria \end{cases} \quad (17)$$

Then, the normalised fuzzy difference is calculated for each couple of criterion and alternative, as shown in Eq. 18.

$$\begin{cases} \widetilde{D}_{ij} = \frac{\tilde{X}_j^* \ominus \tilde{X}_{ij}}{r_j^* - l_j^-} & \forall j\ benefit\ criteria \\ \widetilde{D}_{ij} = \frac{\tilde{X}_{ij} \ominus \tilde{X}_j^*}{r_j^- - l_j^*} & \forall j\ cost\ criteria \end{cases} \quad (18)$$

After the identification of the fuzzy normalised differences, the values of $\tilde{S}_i = (S_i^l, S_i^m, S_i^r)$, $\tilde{R}_i = (R_i^l, R_i^m, R_i^r)$, and $\tilde{Q}_i = (Q_i^l, Q_i^m, Q_i^r)$ are computed according to Eq. 19, Eq. 20, and Eq. 21.

$$\tilde{S}_i = \sum_{j=1 \oplus}^{c} \widetilde{W}_j \otimes \widetilde{D}_{ij} \quad (19)$$

$$\tilde{R}_i = \max_j (\widetilde{W}_j \otimes \widetilde{D}_{ij}) \quad (20)$$

$$\tilde{Q}_i = \upsilon \frac{\tilde{S}_i \ominus \tilde{S}^*}{S^{-r} - S^{*l}} + (1 - \upsilon) \frac{\tilde{R}_i \ominus \tilde{R}^*}{R^{-r} - R^{*l}} \quad (21)$$

where $\tilde{S}^* = \min_i \tilde{S}_i$, $S^{-r} = \max_i S_i^r$, $\tilde{R}^* = \min_i \tilde{R}_i$, $R^{-r} = \max_i R_i^r$, while υ is a user-defined parameter, which is the weight of the maximum group utility. Finally, the defuzzification of $\tilde{S}_i$, $\tilde{R}_i$, and $\tilde{Q}_i$ could be performed based on Eq. 22 [25]. Through the defuzzied values, it is possible to define three ranks. Specifically, the alternatives can be ranked based on the crisp values of S,

R, and Q.

$$Crisp(\tilde{A}) = \frac{l+2*m+r}{4} \tag{22}$$

The compromise solution would be the one ranked as first for Q. However, the conditions of acceptable advantage and acceptable stability in decision-making are met. The first condition can be verified through Eq. 23, while the latter is verified in case the best alternative for Q is also the best alternative for at least one between R and S.

$$Q\left(A^{(2)}\right) - Q\left(A^{(1)}\right) \geq DQ \tag{23}$$

where $Q\left(A^{(1)}\right)$, $Q\left(A^{(2)}\right)$ are the alternatives ranked in first and second position for Q, respectively, while DQ = 1/(M-1) or 0.25 if $M \leq 4$ [18]. In case Eq. 23 is not verified, a set of compromised solutions is obtained through $Q\left(A^{(\mathrm{N})}\right) - Q\left(A^{(1)}\right) < DQ$ for maximum N.

IV. DEVELOPED METHODOLOGY

The tools described in Section III are combined as shown in Figure 1

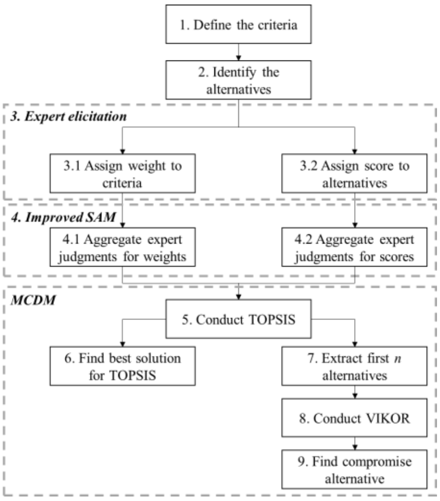

Figure 1 flowchart of the developed framework

First, the criteria based on which the alternatives should be evaluated are defined (step 1). Next, the alternatives to study are identified (step 2). Experts are asked to express two kinds of judgments: the importance of each given criterion (step 3.1), and the score of each alternative with respect to each criterion (step 3.2). The linguistic and fuzzy scales adopted to conduct step 3.1 and step 3.2 are listed in Table I and Table II, respectively (elaborated from Junior et al. [26]). Then, the opinions arising from different experts are aggregated through the improved SAM (see Section III-A). Specifically, the improved SAM is used for both the criteria weight (step 4.1) and the score of the alternatives (step 4.2). It is worth mentioning that the weight of each expert is evaluated following Guo et al. [21]. Based on the aggregated weight of each criterion and the aggregated rate of each alternative with respect to each criterion, the fuzzy TOPSIS is conducted. The fuzzy TOPSIS provides a ranking of the considered alternatives, allowing to identify the best solutions (step 6). Even though the former steps could be sufficient to identify the most suitable alternative, at least two MCDM approaches should be adopted to evaluate the consistency of the results [27]. Accordingly, a subset of the best alternatives depicted by the fuzzy TOPSIS (e.g., the first 5) is extracted (step 7). The subset is processed through a fuzzy VIKOR (step 8). Indeed, fuzzy VIKOR not only establishes a new ranking, but it can also provide a compromise alternative (step 9).

TABLE I
LINGUISTIC AND FUZZY SCALES TO EVALUATE THE WEIGHT OF EACH CRITERION

Linguistic term	Fuzzy TFN
Of little importance (OL)	(0,0,0.25)
Moderately Importance (MI)	(0,0.25,0.5)
Important (I)	(0.25,0.5,0.75)
Very Important (VI)	(0.5,0.75,1)
Absolutely Important (AI)	(0.75,1,1)

TABLE II
LINGUISTIC AND FUZZY SCALES TO EVALUATE THE RATE OF EACH ALTERNATIVE

Linguistic term	Fuzzy TFN
Very Low (VL)	(0,0,0.25)
Low (L)	(0,0.25,0.5)
Good (G)	(0.25,0.5,0.75)
High (H)	(0.5,0.75,1)
Very high (VH)	(0.75,1,1)

V. RESULTS: APPLICATION OF THE METHODOLOGY

A. *Expert elicitation and improved SAM*

To describe the implementation of the framework, a cement plant is considered as case study. Indeed, the cement industry could be considered as highly energy intensive. Thus, reducing the energy requirements of a cement plant is very important.

Specifically, three criteria are chosen to evaluate different alternatives. Specifically, the selected criteria related to energy-saving are the following ones (step 1): electricity saving (c_1), thermal saving (c_2), and fuel saving (c_3). On the other hand, four alternatives are considered in this study (step 2): replacing compressors with newer ones (A_1), installing a heat recovery system (A_2), replacing engines with newer ones or installing inverters (A_3), and install more efficient machines in the production line (A_4).

A group of three experts is asked to express judgments related to the importance of each criterion (step 3.1) and the performance of each alternative with respect to each criterion (step 3.2). The results are shown in Table III and

Table IV, respectively.

TABLE III
WEIGHT ASSOCIATED WITH EACH CRITERION

Criterion	E1	E2	E3
C1	AI	VI	AI
C2	I	I	MI
C3	MI	OL	I

TABLE IV
RATE OF EACH ALTERNATIVE WITH RESPECT TO EACH CRITERION

Expert	Alternative	Criterion		
		C1	C2	C3
E1	A_1	G	VL	VL
	A_2	VH	G	H
	A_3	L	VL	VL
	A_4	G	VH	L
E2	A_1	L	VL	L
	A_2	VH	L	G
	A_3	G	VL	L
	A_4	G	VH	VL
E3	A_1	L	VL	L
	A_2	VH	L	H
	A_3	L	VL	L
	A_4	G	H	VL

Based on the improved SAM presented in Section III-A, both the weights of criteria (step 4.1) and the rates of the alternatives are aggregated (step 4.2), considering the fuzzy scales listed in Table I and Table II, respectively. The former steps are conducted considering a relaxation factor equal to 0.5 since it is one of the most popular values [28]. The aggregation leads to the results shown in Table V (for the weights) and Table VI (for the rates).

TABLE V
AGGREGATED TFN FOR THE WEIGHT OF EACH CRITERION

Criterion	Aggregated weight
C1	(0.662, 0.912, 1)
C2	(0.169, 0.419, 0.669)
C3	(0.082, 0.243, 0.493)

TABLE VI
AGGREGATED TFN FOR THE RATE OF EACH ALTERNATIVE WITH RESPECT TO EACH CRITERION

Alternative	Criterion		
	C1	C2	C3
A_1	(0.069, 0.319, 0.569)	(0, 0, 0.25)	(0, 0.179, 0. 429)
A_2	(0.75, 1, 1)	(0.069, 0.319, 0.569)	(0.413, 0.663, 0.913)
A_3	(0.087, 0.337, 0.587)	(0, 0, 0.25)	(0, 0.179, 0. 429)
A_4	(0.25, 0.5, 0.75)	(0.668, 0.918, 1)	(0, 0.071, 0.321)

B. Application of fuzzy TOPSIS

The aggregated TFNs listed in Table V and Table VI are used as input to carry out the fuzzy TOPSIS (step 5). Indeed, Table V reports the vector of weights ($\widetilde{W}$), while Table VI could be seen as the initial decision matrix (D). Thus, the decision matrix is first normalised through Eq. 8, and, subsequently, the weighted normalised decision matrix is obtained according to Eq. 9. After estimating FPIS and FPIN based on Eq. 10 and 11, respectively, d_i^* and d_i^- are computed for each alternative. The distances from the FPIS and the FPIN of each alternative are listed in Table VII. Finally, Eq. 15 allows estimating the Closeness Coefficient, which is exploited to rank the alternatives. The Closeness Coefficient associated with each alternative and the related rank are shown in Table VII as well.

TABLE VII
DISTANCE FROM FPIS AND FPIS, CLOSENESS COEFFICIENT, AND RANK OF EACH ALTERNATIVE

Alternative	d_i^*	d_i^-	C_{coeff}	Rank
A_1	1.048	0.038	0.035	4
A_2	0.228	0.860	0.790	1
A_3	1.033	0.053	0.049	3
A_4	0.563	0.528	0.484	2

Following Table VII, it is possible to state that TOPSIS ranked as first A_2, which means that installing a heat recovery system is the preferable solution among the four (step 6) to reduce the energy consumption in cement industries. Furthermore, A_4 (i.e., installing more efficient machines in the production line) is the second most preferable solution. Finally, replacing compressors with newer ones (A_1) and replacing engines with newer ones (A_3) are depicted as the least suitable alternatives based on the considered criteria and their relative importance.

C. Application of fuzzy VIKOR

The framework presented in Fig. 1 specifies to select a subset of alternatives (step 7). Specifically, the user should specify the number of alternatives to consider for the following fuzzy VIKOR as an ordered subset of the best alternatives depicted by the TOPSIS. For instance, the user could consider the alternatives ranked from the first to the fifth. Defining a sub-group of alternatives is not mandatory, but it could be useful to focus on a lower number of alternatives that were previously ranked by another MCDM approach. For the present case study, due to the low number of considered alternatives, all four alternatives are processed through the fuzzy VIKOR (step 8).

The fuzzy VIKOR exploits as input the same aggregated TFNs used for the fuzzy TOPSIS. Specifically, the fuzzy VIKOR considers both Table V and Table VI. Following the steps described in Section III-C, the ideal and nadir solutions are estimated for each criterion based on Eq. 16 and Eq. 17. After the estimation of the normalised fuzzy difference (see Eq. 18), the utility ($\tilde{S}_i$) and regret ($\tilde{R}_i$) values are computed for each alternative. The obtained fuzzy utility and regret values along with the corresponding crisp numbers (see Eq, 2) are listed in Table VIII and Table IX, respectively. Table VIII and Table IX report also the rank based on $\tilde{S}_i$ and $\tilde{R}_i$.

TABLE VIII
FUZZY AND CRISP VALUES OF $\tilde{S}_i$, WITH THE ASSOCIATED RANK

	S_i^l	S_i^m	S_i^r	S crisp	Rank
$\tilde{S}_1$	0.198	1.180	2.162	1.180	4
$\tilde{S}_2$	-0.206	0.251	1.161	0.364	1
$\tilde{S}_3$	0.185	1.163	2.142	1.163	3
$\tilde{S}_4$	-0.048	0.647	1.520	0.692	2

TABLE IX
FUZZY AND CRISP VALUES OF $\tilde{R}_i$, WITH THE ASSOCIATED RANK

	R_i^l	R_i^m	R_i^r	R crisp	Rank
$\tilde{R}_1$	0.129	0.667	1.000	0.616	4
$\tilde{R}_2$	0.017	0.251	0.623	0.285	1
$\tilde{R}_3$	0.116	0.649	0.981	0.599	3
$\tilde{R}_4$	0.008	0.490	0.806	0.448	2

Using Eq. 21, the value of $\tilde{Q}_i$ and the associated rank is estimated for each alternative as shown in Table X. To conduct this step, the weight of the maximum utility (υ) is taken equal to 0.5, as the typical adopted value [29].

TABLE X
FUZZY AND CRISP VALUES OF $\tilde{Q}_i$, WITH THE ASSOCIATED RANK

	Q_i^l	Q_i^m	Q_i^r	Q crisp	Rank
$\tilde{Q}_1$	-0.453	0.406	1.000	0.340	4
$\tilde{Q}_2$	-0.594	0.000	0.599	0.001	1
$\tilde{Q}_3$	-0.462	0.393	0.986	0.328	3
$\tilde{Q}_4$	-0.565	0.204	0.767	0.152	2

As depicted in Table XI, A_2 (i.e., installing a heat recovery system) is the compromise alternative (step 9). Furthermore, A_2 emerges also as the best alternative for both $\tilde{S}_i$ and $\tilde{R}_i$. Accordingly, the condition of acceptable stability is verified. Finally, considering the condition of acceptable advantage, A_2 and A_4 emerged as compromise solutions.

VI. DISCUSSION

The proposed framework is able to provide a ranking of the different alternatives, which could be exploited as a guideline for the decision-making process related to energy-saving investments. For the considered case study, the integration of the improved SAM and the fuzzy TOPSIS led to the following ranking $A_2 > A_4 > A_3 > A_1$. Accordingly, the best energy-saving solution would be A_2, which is the installation of a heat recovery system. This is aligned with previous studies which identified the heat recovery systems as common implemented solutions in energy-intensive plants [4]. Indeed, high temperatures are reached in a cement plant, thus the exhaust gases could still maintain a high degree of heat, which could be seen as a loss of the process. A heat recovery system could allow to retrieve the heat, increasing the efficiency of the production. On the other hand, the replacement of engines and compressors with newer ones (respectively A_3 and A_1) are depicted as the worst alternatives. As a matter of fact, the installation of newer and more efficient engines or compressors could allow reducing the electric energy or fuel requirements, but the saving is often limited. However, it is worth mentioning that only energy-saving criteria were considered for the analysis (i.e., electric energy saving, thermal energy saving, and fuel saving). Even though the replacement of engines and compressors is not so profitable in terms of energy savings, it is associated with the lowest cost among the considered investments. However, the cost was not considered as a criterion influencing the analysis.

Another interesting finding is that both fuzzy TOPSIS and fuzzy VIKOR determined the same best alternative (i.e., A_2) for the considered case study. In case the decision maker finds a similar scenario could pick the common best alternative. However, it is worth mentioning that different judgments (e.g., arising from different experts or different contexts) could lead to different results. Thus, it is up to the decision maker to pick which is the best alternative between the ones recommended by the TOPSIS and the VIKOR, respectively.

VII. CONCLUSION

Under the current requirements of energy efficiency, selecting the most suitable energy-saving solutions is fundamental. This paper presents a framework to facilitate the former decision-making process thanks to the integration of two popular MCDM methods (i.e., TOPSIS and VIKOR), FST, and the improved SAM. From a theoretical perspective, this work faces the problem of aggregating expert opinions, which is often neglected in the context of MCDM approaches. Specifically, the improved SAM is a robust and objective aggregation method since it allows considering the weight of the experts and their consensus. Furthermore, the adoption of two MCDM tools provides a higher flexibility to the decision maker, other than being preferred to assess the consistency of results when subjectivity is present.

From a practical perspective, the tool proposed in this study could be exploited by any decision maker who wants to rank the performance of different energy-saving solutions with respect to different criteria. This task can be accomplished even without significant information since a set of experts could be consulted to provide missing information or data.

Considering the limitations of this study, it is worth mentioning that a reduced set of criteria and alternatives was considered. Accordingly, it could be possible to expand the set of criteria and alternatives to evaluate how more alternatives and criteria influence the final ranking. Furthermore, expert judgments, user-defined parameters, and fuzzy scales could affect the results. Thus, another future avenue could include a sensitivity analysis involving the former factors. Finally, the current approach is tested on a single case study and for a single application. Therefore, considering the developed approach for different case studies and applications could be useful to analyse its weaknesses and strengths further.

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