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A Multi-Agent Decision-Making Model for the Ranking of Energy Storage Technologies

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Energy storage can help in solving the problem of intermittency associated with renewable energy as well as provide a reliable and stable energy supply in the transition to a low carbon society. Energy storage technologies (EST) that are available in the market and in the process of development have their specific strengths and weaknesses. The selection of an EST for a specific application requires the evaluation of its various characteristics. The development of sustainable energy storage necessitates a multi-criteria approach and robust decision support systems. The factors to consider in selecting the best EST from multiple alternatives are energy density, specific energy, cycle efficiency, power density, specific power, technology readiness level (TRL), power/energy capital cost, and lifespan. This study proposes a fuzzy multicriteria decision-making method in a multi-agent environment. A consensus measure is incorporated in the decision model where the evaluation of criteria or alternatives is vague or imprecise. A case study is presented to demonstrate the use of such ranking methodologies which could guide decision-makers in selecting the best EST for stationary power application.

1. Introduction

According to the International Energy Agency (IEA, 2021), the contribution of renewable electricity to the power grid is forecast to increase by 60 % between 2020 – 2026, to about 4,800 GW. This is equivalent to the current combined fossil fuel and nuclear power output in the world. The electricity output from renewable energy (RE) is projected to increase further to achieve the pathway to net zero by 2050. To achieve the committed target in COP26, governments around the world should address policy and implementation challenges for renewable and include investment in energy storage technologies (ESTs). RE still has its shortcomings that can be a hindrance to full integration and implementation in the energy and power grid (Chofrey et al., 2019). The major issue of RE is due to its intermittency which affects its dependability as an alternative energy source. It could be addressed through integration of smart systems of energy storage technologies (Ortenero and Tan, 2021). EST could serve as a buffer during peak energy demand and provide a stable and reliable power supply.
There have been continual progressive improvements in energy storage systems for integration with renewable energy (RE). Various energy systems have a vital role in energy harvesting derived from different sources. This in turn converts these forms of energy to the required functions of application associated with the building, industry, transportation (Chuah et al., 2021), and utility. In thermal power plants, energy generated from fossil fuel can be readily used according to customer demand. However, other RE sources that include wind and solar require harvesting and proper storage until the demand is needed. The application of energy storage has multiple benefits in its energy systems. This includes the following: 1) good economic performance, 2) allowing substantial penetration of RE, 3) essential towards electrical systems for damping energy oscillations, proper peak shaving and load leveling, regulated frequency, 4) and refined power reliability and quality (Gielen et al., 2019).
Various forms of energy storage systems have been introduced and they are categorized according to the type of energy transformation from electricity generated from RE to storage. Among these classifications are mechanical energy storage (MES), electrochemical energy storage (EES), chemical energy storage (CES), electrical and magnetic energy storage (EMES), and thermal energy storage (TES). EST can be further

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classified based on the chemical composition of the active materials, mode of storage, and type of chemical storage (Koohi-Fayegh and Rosen, 2020). The performance of ESTs varies widely depending on the type and level of development. One way to evaluate ESTs is to check its performance with respect to characteristics such as power density, energy density, specific energy/power, life cycle, efficiency, technology readiness level, environmental impact, and power and energy capital cost. The type of application is a major consideration such that a specific criterion could play a critical role in the selection. For instance, for space-constrained applications in urban areas, compact, light, and modular type are most preferable, so high specific and volumetric energy/power density are dominant factors to be considered. The storage energy density and power density are important aspects to consider to appropriately evaluate the energy accumulation and energy transfer per unit mass/volume. In areas of abundant land and with the right geographical features, specific energy/power capital cost could be the dominant criteria.

This study is carried out to use a proposed innovative method in ranking energy storage technologies as illustrative case study. Three experts have been involved in the decision-making process that entail value judgments and uncertain data for the complex problem in the case study. The novel application in the fuzzy multi-criteria decision making under a multi-agent environment is to rank several ESTs based on the rating of these experts. This then highlights the spherical fuzzy extension of simple additive weighting to rank the alternatives with the simultaneous methods of the spherical analytic hierarchy process (SFAHP) and spherical fuzzy additive weighting (SFAW) to derive the criteria weights for weighted performances and the fuzzy evaluation matrix (Gündoğdu and Kahraman, 2019). Spherical fuzzy set is an essential component to model uncertainty in human opinion, which is the most recent extension of Zadeh's fuzzy set by expressing fuzziness into three components namely membership degree, non-membership degree and indeterminacy degree under the condition that the sum of squares of these components is less than one (Mahmood et al., 2019). A generated defuzzification of the spherical fuzzy score is then used to rank the alternative that leads to the computation of the consensus. A group-aggregated score to rank the alternatives can then be achieved by the experts through a quick and efficient method in arriving with a linguistic rating.

2. Methodology

2.1 Preliminaries

This section introduces the definitions related to spherical fuzzy set and its generalization, T-spherical fuzzy set.

Definition 1. Let X be in a finite domain and $x \in X$. T-spherical fuzzy set (TSFS) is defined as: $T = \{x, \mu(x), \nu(x), \pi(x) \mid x \in X\}$ with the condition that $0 \leq Sum(\mu^t, \nu^t, \pi^t) \leq r^t \; \forall \; t \in Z \geq 1$. Here three components $\mu, \nu, \pi: X \rightarrow [0,1]$ represents the degree of membership, degree of non-membership, and degree of indeterminacy. Z refers to positive integers and $r^t \rightarrow [1, 3^{1/t}]$. Note that $r^t = 1$ is a particular case of T in X, for example is a spherical fuzzy set (SFS) at t = 2 with the condition of $0 \leq Sum(\mu^2, \nu^2, \pi^2) \leq 1$, i.e., $0 \leq \mu^2 + \nu^2 + \pi^2 \leq 1$. For ease of computation, T-spherical fuzzy number is designated as an ordered triple: $\tilde{T}_s = (\mu_{\tilde{T}_s}, \nu_{\tilde{T}_s}, \pi_{\tilde{T}_s})$.

Definition 2. T-spherical weighted geometric mean (TSWGM) is an aggregation operator for n T-spherical fuzzy numbers using weighted geometric mean such that the weight vector $w_i \in [0,1]$; $\sum_{i=1}^{n} w_i = 1$.

$TSWGM(\tilde{T}_{s1} \ldots \ldots \tilde{T}_{sn}) = \Pi_{i=1}^{m} (\tilde{T}_{sn})^{w_i}$ =

$$\left\{ \prod_{i=1}^{n} \mu_{\tilde{T}_{si}}^{w_i}, \left[1 - \prod_{i-1}^{n} \left(1 - \nu_{\tilde{T}_{si}}^{t}\right)^{w_i}\right]^{\frac{1}{t}}, \prod_{i=1}^{n} \pi_{\tilde{T}_{si}}^{w_i}, \right\} \tag{1}$$

Definition 3. T-spherical weighted arithmetic mean (TSWAM) is an aggregation operator for n T-spherical fuzzy numbers using weighted arithmetic mean such that the weights $w_i \in [0,1]$; $\sum_{i=1}^{n} w_i = 1$.

$TSWAM_w(\tilde{T}_{s1} \ldots \ldots \tilde{T}_{sn}) = w_1 \tilde{T}_{s1} + w_2 \tilde{T}_{s2} + \cdots + w_n \tilde{T}_{sn} = \sum_{i=1}^{n} w_i \tilde{T}_{Si}$=

$$\left\{ \left[1 - \prod_{i-1}^{n} \left(1 - \mu_{\tilde{T}_{si}}^{t}\right)^{w_i}\right]^{\frac{1}{t}}, \prod_{i=1}^{n} \nu_{\tilde{T}_{si}}^{w_i}, \prod_{i=1}^{n} \pi_{\tilde{T}_{si}}^{w_i} \right\} \tag{2}$$

Definition 4. Defuzzification of T-spherical fuzzy number is defined as follows:

$$Score(\tilde{T}) = 1 - \left[\frac{1}{3}\left\{(1 - \mu^t)^\beta + (\nu^t)^\beta + (\pi^t)^\beta\right\}\right]^{1/\beta} \tag{3}$$

where $\beta \geq 1$ is the distance parameter. Here the $Score(\tilde{T}) \rightarrow [0,1]$.

2.2 Fuzzy Multiple Criteria Decision-Making (MCDM) with consensus measure

The proposed method in a step-by-step procedure is depicted in Figure 1.

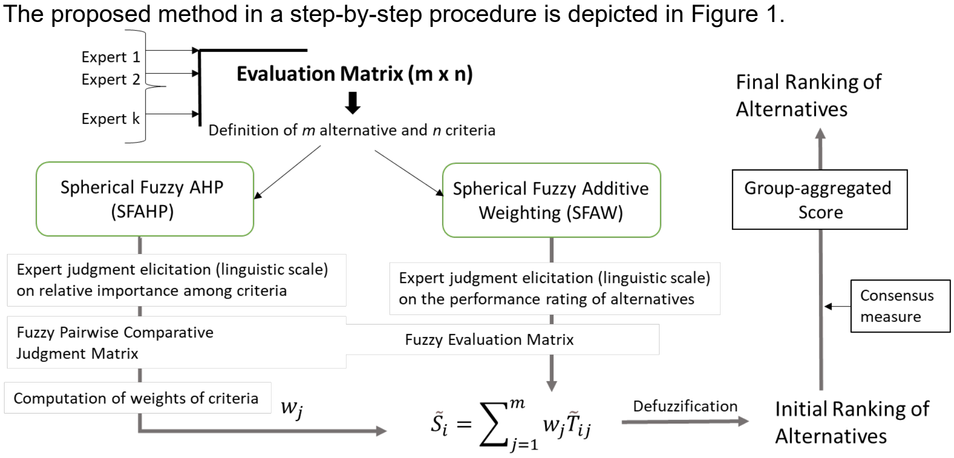

Figure 1. Procedural flow of the proposed fuzzy MCDM under multiple agents

The procedures are as follows:

Step 1: Create the evaluation matrix by defining *m* alternatives and *n* criteria.

Step 2: Elicit from each expert the relative importance (see Table 1) of *n* criteria to populate the spherical fuzzy pairwise comparison matrix. The a_{ij} represent the relative importance rating of row criteria *i* over the column criteria *j*. The a_{ji} is the inverse of a_{ij}. For example, if criteria *i* is strongly more important (STM) than criteria *j*, then criteria *j* is strongly less important (STL) than criteria *i*. Just like the classic AHP, the matrix requires *n(n-1)/2* pairwise comparative judgments. Note that the entries in the diagonal (a_{ii}) is automatically set to EQ rating, i.e, criteria *i* is equally important to criteria *i*. To compute the weights, the importance rating is transformed to the spherical fuzzy number described in Table 1. Details of computation is described elsewhere (Kuok and Promentila, 2021).

Step 3: Elicit from each expert the performance rating of the alternatives to populate the individual fuzzy evaluation matrix $Z = [z_{ij}]_{mxn}$. In this matrix, the number of rows corresponds the number of alternatives whereas the number of columns corresponds the number of criteria. Use the linguistic scale provided in Table 1 for the performance rating. Let $\tilde{T}_{ij}$ as the entry to z_{ij} to describe the performance rating of alternative i with respect to criteria j as represented by a spherical fuzzy number.

Step 4: Calculate the composite score of the alternatives from evaluation matrix using SFAW which is analogous to simple additive weighting (SAW) method. This can be done by finding the sum of the weights of the performance rating on each alternative on all criteria so that it can determine the best alternative. Since the performance rating is in a form spherical fuzzy number, the spherical fuzzy set extension of SAW is defined by the following equation:

$$\tilde{S}_i = \sum_{j=1}^{m} w_j \tilde{T}_{ij} \text{ , } \forall\, i = 1 \dots m \qquad (4)$$

where $\tilde{S}_i$ is the total spherical fuzzy score of alternative *i* and the criteria weight vector $w_j \in [0,1]$; $\sum_{i=1}^{n} w_j = 1$.

$$\left\{ \tilde{S}_i = (\mu_{\tilde{S}_i}, v_{\tilde{S}_i}, \pi_{\tilde{S}_i}) = \left[1 - \prod_{i-1}^{n}\left(1 - \mu_{\tilde{T}_{ij}}^2\right)^{w_j}\right]^{\frac{1}{2}}, \prod_{i=1}^{n} v_{\tilde{T}_{ij}}^{w_j}, \prod_{i=1}^{n} \pi_{\tilde{T}_{ij}}^{w_j} \right\} \qquad (5)$$

Eq(5) uses the aggregation operation described in Eq(2) at t = 2 for spherical fuzzy set.

Step 5: Defuzzification of the spherical fuzzy score to rank the alternatives. Eq(3) at $t = 2$ is used to compute the crisp score ($\bar{S}_i$) of the alternatives. The distance parameter β is set to 19/8 to give a score of 0.50 to a satisfactory rating with a spherical fuzzy number (0.50, 0.50, 0.50). The higher the score, the closer the alternative to the ideal alternative. Thus, the highest score is ranked 1st, followed by the second highest score, and so on.

Step 6: Compute the consensus measure using the Kendall's W or coefficient of concordance (Kendall and Smith, 1939). The ranking of alternatives from each expert are used as input in the calculation to measure the degree of agreement among experts. A Kendall's W of 0.60 or higher suggests strong consensus while a Kendall's W of lower than 0.30 suggests weak consensus.

Step 7: Compute the group-aggregated score from *k* experts ranking of alternatives using the following equation:

$$S_i = \sum_{h=1}^{k} w_h \bar{S}_i \,, \forall\, i = 1 \ldots m \text{ and expert weight vector } w_h \in [0,1];\ \sum_{h=1}^{k} w_h = 1 \quad (6)$$

The highest group-aggregated score is ranked 1st.

Table 1: Linguistic scale used in this study with the corresponding spherical fuzzy numbers

Performance Rating	(μ, v, π)	Relative Importance Rating	(μ, v, π)
Excellent (EX)	(0.90, 0.10, 0.10)	Very highly more important (VSM)	(0.90, 0.10, 0.10)
Very good (VG)	(0.80, 0.20, 0.25)	Strongly more important (STM)	(0.80, 0.20, 0.25)
Good (GD)	(0.70, 0.30, 0.35)	Moderately more important (MM)	(0.70, 0.30, 0.35)
Slightly good/Above satisfactory (AS)	(0.60, 0.40, 0.40)	Slightly more important (SM)	(0.60, 0.40, 0.40)
Moderate/Satisfactory (S)	(0.50, 0.50, 0.50)	Equally important (EQ)	(0.50, 0.40, 0.40)
Slightly bad/Below Satisfactory (BS)	(0.40, 0.60, 0.40)	Slightly less important (SL)	(0.40, 0.60, 0.40)
Bad (BD)	(0.30, 0.70, 0.35)	Moderately less important (ML)	(0.30, 0.70, 0.35)
Very bad (VB)	(0.20, 0.80, 0.25)	Strongly less important (STL)	(0.20, 0.80, 0.25)
Worst (WO)	(0.10, 0.90, 0.10)	Very strongly less important (VSL)	(0.10, 0.90, 0.10)

3. Case Study

Energy storage is seen as the solution to provide a buffer between supply and demand by storing the excess energy generated during lean season and providing additional capacity during peak energy consumption. Several energy storage technologies are available that can be used to provide frequency regulation, stability in energy supply from RE, and damping energy oscillations. The ESTs that are considered in this study are flywheel energy storage (FWES) and pump hydro energy storage (PHES), which are forms of MES. The other ESTs are lithium-ion battery (LIB) and sodium-sulfur battery (SSB), which are under EES classification. There are other types of ESTs, but these are considered the most popular, display superior properties in storing energy, and technological maturity, which are important for effective storage of energy from RE.

Table 2: Evaluation matrix of the four alternative ESTs by four criteria

E1				
Energy Storage Technology (EST)	Specific Energy Density	Efficiency	Cycle Life	Energy Capital Cost
FWES	S	GD	VG	VB
PHES	BD	BS	BD	EX
LIB	GD	GD	WO	BS
SSB	EX	GD	VB	GD
E2				
Energy Storage Technology	Specific Energy Density	Efficiency	Cycle Life	Energy Capital Cost
FWES	AS	EX	EX	WO
PHES	VB	GD	EX	VG
LIB	EX	EX	GD	S
SSB	VG	GD	AS	AS
E3				
Energy Storage Technology	Specific Energy Density	Efficiency	Cycle Life	Energy Capital Cost
FWES	GD	VG	VG	BD
PHES	S	GD	VG	VG
LIB	VG	EX	AS	S
SSB	VG	GD	GD	AS

These ESTs are compared to determine the best option for a specific application, for instance in stationary power application. The attributes that are commonly checked for comparison are power density, energy density, specific energy/power, life cycle, efficiency, technology readiness level, environmental impact, and power and energy capital cost. For demonstration of the proposed fuzzy MCDM, the attributes that are considered are specific energy density (Wh/kg), efficiency (%), cycle life (h), and energy capital cost ($/kWh). The rating provided, for example, by three experts or decision makers noted as Expert 1 (E1), Expert 2 (E2), and Expert 3 (E3) are shown in Table 2.

Note that the performance rating is based on the linguistic scale provided in Table 1. For example, E3 rates performance of flywheel energy storage (FWES) as good (GD), very good (VG), very good (VG), and bad (BD) with respect to specific energy density, efficiency, cycle life and energy capital cost, respectively. To rank these alternative ESTs, these ratings will be aggregated through a simple additive weighting to yield a composite score for each alternative. In real multi-agent decision making, each expert will have their own set of weight vectors that will reflect the relative importance of the criteria used for evaluation.

Table 3 provides an example of the pairwise comparison matrix that describe the value judgments of experts in determining the weight vectors of the criteria. For example, E1 thinks that specific energy density is moderately more (MM) important than efficiency. This judgment is reflected from the first row, second column of the pairwise comparison matrix shown in Table 3. Note that these verbal judgments are transformed to spherical fuzzy numbers (μ, v, π) according to Table 1. The weights are then computed using the algorithm of spherical fuzzy AHP (SFAHP) described in Kuok and Promentilla (2021). Result for the criteria weight vectors is summarized in Table 4.

Table 3: Sample pairwise comparison matrix from three decision makers for SFAHP weights

E1				
EST Classification	Specific Energy Density	Efficiency	Cycle Life	Energy Capital Cost
Specific Energy Density	EQ	MM	STM	SM
Efficiency	ML	EQ	STM	MM
Cycle Life	STL	STL	EQ	SL
Energy Capital Cost	SL	ML	SM	EQ
E2				
EST Classification	Specific Energy Density	Efficiency	Cycle Life	Energy Capital Cost
Specific Energy Density	EQ	STM	ML	SL
Efficiency	STL	EQ	MM	SL
Cycle Life	MM	ML	EQ	STM
Energy Capital Cost	SM	SM	STL	EQ
E3				
EST Classification	Specific Energy Density	Efficiency	Cycle Life	Energy Capital Cost
Specific Energy Density	EQ	ML	EQ	ML
Efficiency	MM	EQ	SM	SL
Cycle Life	EQ	SL	EQ	EQ
Energy Capital Cost	MM	SM	EQ	EQ

Table 4: Criteria weights for the specific energy density, efficiency, cycle life, and energy capital cost using fuzzy AHP

Criteria	E1	E2	E3
Specific Energy Density	0.324	0.259	0.197
Efficiency	0.305	0.223	0.283
Cycle Life	0.158	0.292	0.229
Energy Capital Cost	0.213	0.226	0.291

It can be observed in Table 4 that there are differences in the way each expert puts importance on the different criteria, E1 values specific energy density, E2 prefers cycle life, and E3 puts premium on energy capital cost. Thus, the ranking of the alternatives could differ even though the experts may have comparable performance ratings for this set of alternatives.

Table 5 shows the scores obtained from the defuzzification of the spherical fuzzy numbers (μ, v, π) resulted from simple additive weighting of rating for each alternative. The value closest to 1 is the best alternative while the value closest to zero is the worst. It can be observed that there is an agreement between E2 and E3 when it comes to the best (LIB) and worst (SSB) performing EST technology while E1 prefers the fourth EST (SSB) as the best option. Assuming equal weights for the experts, the group-aggregated score is also shown in Table

5. Kendall consensus index with a value W = 0.222 shows that there is weak consensus in the ordinal ranking of the alternatives from the three experts. The consensus among the experts is that the two battery energy storage technologies are the top options for stationary power applications while the two MES lag in performance. It should be noted that the two battery storage technologies have superior properties when it comes to volumetric and specific energy density and efficiency. Lithium-ion battery has the highest volumetric power density which is about sixty times that of second ranked SSB on average. Sodium sulfur battery has slightly higher volumetric and mass energy density and it is more affordable than lithium-ion battery. However, sodium sulfur is not yet widely used compared with lithium-ion but there is great potential for sodium-sulfur to compete with lithium-ion in the future. PHES is the worst technology due to its low volumetric power and energy density while FWES suffers from high cost, about three times that of lithium-ion, while the specific energy density is about one-sixth that of lithium-ion.

Table 5: Ranking of the alternative ESTs

Energy Storage Technology	E1		E2		E3		Group-aggregated	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank
FWES	0.596	2	0.761	2	0.677	3	0.678	3
PHES	0.588	4	0.736	3	0.706	2	0.677	4
LIB	0.595	3	0.781	1	0.730	1	0.702	1
SSB	0.741	1	0.663	4	0.674	4	0.692	2

4. Conclusions

This work applied the fuzzy multi-criteria decision analysis under a multi-agent environment to rank the energy storage technologies based on the following four criteria: specific energy density, efficiency, cycle life, and energy capital cost. The relative importance of the criteria was made explicit using the process of spherical fuzzy AHP. Ranking is based on the composite scores obtained from the spherical fuzzy evaluation matrix. Though the group consensus measure indicates a weak consensus, the group-aggregated score indicates that lithium-ion battery is the best alternative followed closely by sodium-sulfur battery. The worst technology based on fuzzy MCDA methodology is PHES due to its low volumetric power and energy density. Future work includes extending the methodology to more EST alternatives, consider more criteria to gauge the overall performance of the technologies, and include more experts in the decision-making process. This methodology could serve as a guide to decision-makers in the selection of appropriate energy storage technology that could be integrated to existing or future installation of renewables.

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