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Lessons learned from the COVID-19 pandemic in planning the future energy systems of developing countries using an integrated MCDM approach in the off-grid areas of Bangladesh

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ABSTRACT

The COVID-19 epidemic is impeding energy development in developing countries and exacerbating the problems associated with energy planning in off-grid locations. To address such complicated decision-making issues and consider scenarios during this long-lasting pandemic, this study proposes a novel integrated MCDM (Multi-Criteria Decision Making) approach using the Delphi based FO-BWM (Fuzzy Optimistic Best-Worst Method), IDOCRIW (Integrated Determination of Objective Criteria Weights) and the Aggregated Weighting Method integrated with the CoCoSo method under different normalization methods based on a case study of the off-grid areas in Bangladesh. The results of Delphi analysis showed that a total of five criteria were agreed upon by the expert panel. After integrating 5 normalization methods with CoCoSo and using three weighting methods separately, a total of 15 MCDM models were constructed. Finally, the 8 sorted MCDM models demonstrate that Solar Home System (SHS) and Mini-Grid systems need to be prioritized, and the criterion Opportunity of Local Funding (OLF) is essential for choosing between SHS and Mini-Grid systems. Sensitivity analysis showed that the proposed method is effective for easing the dilemmas of energy planning in off-grid areas and provides useful insight to address the impacts of future pandemics on energy planning.

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1. Introduction

The global COVID-19 outbreak has slowed the demand and development of renewable energy technologies, and thereby reduced investment in renewable energy, leading to the loss of many jobs [1,2]. In this context, developing countries are exposed to more sustainable development challenges and economic implications than developed countries [3]. Moreover, in the off-grid areas of developing countries, the dilemma of whether to extend the existing grid or adopt off-grid energy systems has been further worsened due to the impact of the pandemic. Renewable energy, both short-term and long-term, can bring economic, social, and environmental benefits for all countries, including developing countries [4]. However, the fundamental steps in legislation, and socio-political developments for renewable energy are challenges in developing countries, in which the development of UN SDG7 (Sustainable Development Goal for Affordable and Clean Energy) is under great threat [5,6]. As for remote areas in developing countries, off-grid energy systems have potential to benefit small off-grid communities and are socially acceptable and environmentally friendly [7]. However, some studies have established the fact that off-grid energy systems are not economical in developing countries compared with grid connected renewable and conventional energy systems [8–10]. Such conflict has been further worsened by the COVID–19 pandemic, as some local factors could affect the future planning process. For example, the cost of off-grid energy systems or urgent installation of power plants could be critical as most developing countries lack local funds; meanwhile, the time consuming expansion of grid connected energy cannot fulfill the urgent and special needs in the hospitals of rural areas. Therefore, the impact of the pandemic should be properly addressed when making decisions among the options of grid connected renewable,
off-grid and conventional energy systems in off-grid areas; and the lessons learned from this process will be crucial for the progress of SDG7 in developing countries. In the case of Bangladesh, the total current power generation installed capacity is 25,187 MW, of which 96.96% (gas 44.98%, oil 29.17%, coal 7.02%, imported 4.61% and captive 11.12%) of electricity is generated from fossil fuel and renewables contribute only 3.1% [11]. However, Bangladesh ranks the fourth highest in the rate of off-grid electricity access, showing that the country is dominating in the field of off-grid energy system [12]. For example, the Infrastructure Development Company Limited (IDCOL) has set up 4.3 million SHS (Solar Home Systems) in the rural areas of Bangladesh, which covers 12% of the population [13]. Although electricity production from Mini-Grids is relatively undeveloped in Bangladesh, Mini-Grids may be more economical, consistent, reliable, and could solve real-life economic dispatch problems [14,15]. To promote a clean environment, the GoB (Government of Bangladesh) is also promoting large scale solar park and wind energy systems which will be integrated in the national grid. It has been reported that by 2023 the gas reserve will be depleted unless new gas fields are discovered. Thus, GoB discourages gas based power generation and prioritizes coal power generation for the future, as it is cheaper than other forms of fossil fuel based power generation [16]. As for the off-grid areas, most of them are located in the southern part of the country. Yet, the north eastern part of the country also has off-grid areas that are mainly known as ‘Haor’ areas. Most of these areas are using off-grid energy systems, but due to grid extension a number of off-grid areas have now become on-grid areas. However, it is still necessary to choose between off-grid and on-grid energy systems in the off-grid areas of the country, particularly under the current pandemic situation. Therefore, SHS, Mini-Grids, solar parks, wind and coal based power generation systems can be considered for the off-grid areas of Bangladesh, which needs proper ranking and prioritization to achieve SDG 7. Moreover, the long-lasting impact of COVID-19 pandemic should be furthered considered; and an effective and resilient planning approach should be well developed. Acknowledging the importance of addressing such conflicting objectives and complicated criteria in prioritizing the energy alternatives, researchers often adopt Multiple Criteria Decision Making (MCDM) methods, which can consider the complexity of social, technical, economic, and environmental aspects; and, therefore, this approach is adopted in this study. In recent years, off-grid and on-grid energy systems using MCDM methods have become popular in the field of energy planning and development research. Ramezanzade et al. [17] compared different combinations of on-grid and off-grid energy systems based on a case study in Iran using FUCOM (Full Consistency Method), BWM (Best Worst Method), AHP (Analytic Hierarchy Process), TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) and the EDAS (Evaluation based on Distance from Average Solution) method, where the best hybrid system found had a capacity of 550 kW PV, 500 kW WT, 300 kW DG, 800 kW battery, and a 450 kW converter. Rad et al. [18] implemented Entropy-TOPSIS to find the best technology between on-grid and off-grid energy systems in Iran. The findings of the study showed that integration of solar, wind and biogas was the most inexpensive alternative. Although the inclusion of a fuel cell to the system increased the cost of the system, it improved system efficiency. The findings also revealed that on-grid energy systems are more cost-effective than off-grid energy systems. Nsafon et al. [19] proposed a PDCA (Plan-Do-Check-Act Cycle) cycle based AHP integrated VIKOR (ViSeKriterijumska Optimizacija I Kompromisno Resenje) method to determine the best energy technology in Cameroon, and the hybrid energy system showed its superiority in terms of technical and economic benefit. Rad et al. [18] used TOPSIS to find the best hybrid system in Iran, and the result revealed that on-grid PV/wind turbines were the most cost-effective and sustainable. Ye et al. [20] utilized AHP, CRITIC (Criteria Importance Through inter criteria Correlation), and TOPSIS to identify the most viable hybrid energy system in China, where the results showed that an off-grid energy system was more feasible than an on-grid energy system. Babatunde et al. [21] deployed CRITIC and TOPSIS to identify the best hybrid renewable energy system in Nigeria and showed that PV/Generator/Battery is the best one. These studies have demonstrated a significant amount of findings related to the selection of various energy systems using different MCDM methods. However, none of the above work has focused on specific, category wise energy mix scenarios considering the long-term impact of the COVID-19 pandemic. Inappropriate and unsystematic selection of criteria may cause inconsistency in the final decision, and thus the validity of the overall approach will be at risk [22]. Therefore, the Delphi technique, which was originally created by the RAND Corporation, is used in this study to select the final list of criteria [23]. The technique is used to get accurate data, with the intent to ease the deviation of experts’ opinions by defining the average of the answers obtained [24]. The technique is effective when there is uncertainty and a lack of transparency among the experts regarding selecting criteria. The BWM method proposed by Rezaei [25] is flexible and can solve real-world problems with less computational time and high

**Abbreviations**

| Acronym | Description |
|---------|-------------|
| AHP     | Analytic Hierarchy Process |
| BWM     | Best Worst Method |
| CILOS   | Criterion Impact LOSs |
| CoCoSo  | Combined Compromise Solution |
| COE     | Cost of Energy |
| COPRAS  | Complex Proportional Assessment |
| CRITIC  | Criteria Importance Through Inter criteria Correlation |
| EB      | Environmental Benefit |
| EDAS    | Evaluation based on Distance from Average Solution |
| FUCOM   | Full Consistency Method |
| GoB     | Government of Bangladesh |
| IDCOL   | Infrastructure Development Company Limited |
| IDOCRiW | Integrated Determination of Objective Criteria Weights |
| MCDM    | Multiple Criteria Decision Making |
| OF-BWM  | Optimistic Fuzzy BWM |
| OLF     | Opportunity of Local Funding |
| PDCA    | Plan-Do-Check-Act Cycle |
| PIT     | Project Implementation Time |
| PSM      | Power System Master Plan |
| PSR     | Power Supply Reliability |
| PV      | Photovoltaic |
| SDG     | Sustainable Development Goal |
| SHS     | Solar Home System |
| TOSIPS  | Technique for Order of Preference by Similarity to Ideal Solution |
| UN      | United States |
| VIKOR   | ViSeKriterijumska Optimizacija I Kompromisno Resenje |
transparency [26]. Later, Guo and Zhao [27] proposed the fuzzy BWM method, which is narrated by linguistic terms of experts and can be expressed in triangular fuzzy numbers. The outcome of the fuzzy BWM method shows that it can achieve more desirable ranking for alternatives and has higher comparison consistency than the traditional BWM [27]. Lastly, Dong et al. [28] identified several drawbacks of the fuzzy BWM method and proposed a new fuzzy BWM method, which has higher comparison consistency than fuzzy BWM and traditional BWM. In this method, a mathematical formula is converted into four linear programming formulas by four different methods, where the ‘Optimistic Method’ has higher consistency than the other three methods and also has improved distinctive power compared to the traditional fuzzy BWM [28]. However, the OF-BWM (Optimistic Fuzzy BWM), proposed by Dong et al. [28] has not been applied in the field for energy selection, according to our knowledge.

Moreover, the aggregation of the objective weighting method IDOCRiWiW (Integrated Determination of Objective Criteria Weights) proposed by Zavadskas and Podvezko [29] with OF-BWM increases the accuracy of the weighting method. This is also a new approach. The IDOCRiWiW method is nonbiased in nature. In this method, the intense possible values gained by the entropy method can be recouped by the CILOS (Criterion Impact: LOS) method, which is a major advantage [30]. Additionally, to obtain the most precise weights of the criteria, objective and subjective weighting methods must be combined [31].

On the other hand, the CoCoSo (Combined Compromise Solution) method has not been applied to rank the energy systems in developing countries, particularly Bangladesh. Furthermore, the previous literature has not well demonstrated the effects of different normalization techniques used in the CoCoSo method. The measurement of criteria used in the decision matrix usually refers to different units, e.g., meters/centimeters, dollars, and minutes/hours, and some are arranged in an ordinal scale, which need to be converted through normalization methods into dimensionless parameters that help to achieve the final ranking [32]. Due to the use of different normalization methods in ranking models, the final outcomes vary. This leads to need for further investigation. Nonetheless, CoCoSo is more reliable and stable compared with other related traditional MCDM methods such as TOPSIS, VIKOR, COPRAS, and EDAS [33].

Therefore, new guidelines for energy planners to make or restructure a new Power System Master Plan (PSMP) in off-grids areas considering the long-term impact of the pandemic is crucial to achieve SDG7. Only after obtaining more comprehensive information can energy planners have a good understanding of all the energy alternatives in off-grid areas and then make sound decisions to address the energy dilemmas, while considering the impact of the global pandemic. Thus, based on a case study of the off-grid areas of Bangladesh, this study proposes an integrated MCDM using Delphi based FO-BWM, Aggregated Weighting Method (OF-BWM + IDOCRiWiW), and IDOCRiWiW integrated CoCoSo approach under different local criteria and normalization methods considering the long-term impact of the COVID-19 pandemic. The proposed method is novel in the field of energy. The objectives of this research are therefore threefold: first, to identify the key local criteria that are influential for planning in response to the long-term impact of the COVID-19 pandemic through the Delphi approach and check whether experts agree about the selection of these criteria; second, to calculate the weights of the criteria using the proposed method to rank the energy systems and then integrate all fifteen models to find the best models; and third, to discuss the lessons learned based on the results of two types of sensitivity analysis.

2. Methodology

2.1. Framework and process in the integrated MCDM

To conduct the analysis, initially, a number of criteria were selected from different studies and reports and based on the COVID-19 situation. The values based on the different criteria for the data collected were both quantitative and qualitative, where quantitative data were obtained from a secondary source, and qualitative data were drawn from the experts’ rating. After using the Delphi method, five criteria were chosen for the planning. Then the weights of those criteria were obtained by OF-BWM, IDOCRiWiW, and the Aggregated Weighting Method. Next, five normalization methods, namely Max-Min Linear (N1), Linear Max (N2), Linear Sum (N3), Vector (N4), and Logarithmic (N5), were integrated using the CoCoSo method considering each weighting method separately. Thus, 15 models were formed and named as M1: OF-BWM-CoCoSo (N1), M2: OFBWM-CoCoSo (N2), M3: OFBWM-CoCoSo (N3), M4: OFBWM-CoCoSo (N4), M5: OFBWM-CoCoSo (N5), M6: Aggregated-CoCoSo (N1), M7: Aggregated-CoCoSo (N2), M8: Aggregated-CoCoSo (N3), M9: Aggregated-CoCoSo (N4), M10: Aggregated-CoCoSo (N5), M11: IDOCRiWiW-CoCoSo (N1), M12: IDOCRiWiW-CoCoSo (N2), M13: IDOCRiWiW-CoCoSo (N3), M14: IDOCRiWiW-CoCoSo (N4) and M15: IDOCRiWiW-CoCoSo (N5). Finally, two types of sensitivity analysis were conducted to understand the validity of the proposed approach. The conceptual framework of the study is shown in Fig. 1.

2.2. Delphi

To select the most important criteria, we applied the Delphi method. The process of this method is explained below.

Step 1: Establish a list of initial decision criteria \( C = \{C_1, C_2, C_3, \ldots, C_n\} \).

Step 2: Send the list of criteria \( C = \{C_1, C_2, C_3, \ldots, C_n\} \) to the expert panels.

Step 3: Calculate the Coefficient of Variation (CV). When, the 0 ≤ CV ≤ 0.50 condition is fulfilled, the survey is stopped [34].

Step 4: Calculate the modified Kappa \( (K^*) \) to check the level of understanding among the decision makers about the selected criteria [35].

\[
K^* = \frac{ICVI - p_c}{1 - p_c}
\]

where ICVI is the proportion of agreements on relevance and \( p_c \) is the probability of chance occurring.

Step 5: Confirm the list of criteria \( C = \{C_1, C_2, C_3, \ldots, C_n\} \).

2.3. OF-BWM

To estimate the weights of the criteria, we applied FO-BWM. The following procedure was used to calculate the weights.

Step 1: Find the best (most desirable) \( C_B \) and worst (least desirable) \( C_W \) criterion [25] (see Table 1).

Step 2: Compute the fuzzy Best-to-Others vector \( \tilde{A}_B = [\tilde{a}_{B1}, \tilde{a}_{B2}, \tilde{a}_{B3}, \ldots, \tilde{a}_{Bn}] \) and Others-to-Worst vector \( \tilde{A}_W = [\tilde{a}_{W1}, \tilde{a}_{W2}, \tilde{a}_{W3}, \ldots, \tilde{a}_{Wn}] \), where Table 2 is used to rate the criteria [27].

Regarding the fuzzy Best-to-Others vector, \( \tilde{a}_{Bj} \) symbolizes the
fuzzy preference of the best criterion \( C_W \) over criterion \( C_j \), \( \tilde{a}_{Wj} = (d_{Wj}, a_{Wj}^u, a_{Wj}^l), j = 1, 2, 3, \ldots, n \) and \( \tilde{a}_{WW} = (1, 1, 1) \). On the other hand, regarding the Others-to-Worst vector, \( \tilde{a}_{Wj} \) symbolizes the fuzzy preference of the best criterion \( C_W \) over criterion \( C_j \). \( \tilde{a}_{Wj} = (d_{Wj}, a_{Wj}^u, a_{Wj}^l), j = 1, 2, 3, \ldots, n \) and \( \tilde{a}_{WW} = (1, 1, 1) \).

**Step 3**: Set the parameters \( d_{tj} = q_{tj} = 1, (j = 1, 2, 3; t = l, m, u) \).

From Step 4 to Step 9, we adopted the optimistic approach [28].

**Step 4**: Construct the linear programming model.

**Step 5**: Solve the linear model and calculate the optimal fuzzy weight vector \( \tilde{w} = (\tilde{w}_1, \tilde{w}_2, \tilde{w}_3, \ldots, \tilde{w}_n) \).

**Step 6**: Calculate fuzzy deviation \( \xi^* = (\xi^l, \xi^m, \xi^u) \) using the following equation.

\[
\begin{align*}
\xi^l &= \min(\xi^l, \xi^m, \xi^u), \\
\xi^m &= \text{median}(\xi^l, \xi^m, \xi^u), \\
\xi^u &= \max(\xi^l, \xi^m, \xi^u) \\
\end{align*}
\]

Where,

\[
\begin{align*}
\xi^l &= \frac{1}{2n} \sum_{j=1}^{n} \left( |w^l_{Bj} - w^l_{Wj}a_{Wj}^l| + |w^l_{aj} - w^m_{aj}a_{aj}^m| \right) \\
\xi^u &= \frac{1}{2n} \sum_{j=1}^{n} \left( |w^m_{Bj} - w^u_{Wj}a_{Wj}^u| + |w^u_{aj} - w^l_{aj}a_{aj}^l| \right)
\end{align*}
\]
from equation (3).

Values of FCI.

Where $h$ is the entropy constant and is denoted as $h = \frac{1}{\ln(m)}$ and $\ln r_{ij}$ is defined as 0 if $r_{ij} = 0$.

### Step 3: Calculate the entropy weight.

$$W_j = \frac{d_j}{\sum_{j=1}^{n} (d_j)}$$

where, $d_j$ denotes the degree of diversification and is expressed as $d_j = 1 - E_j$.

### Step 4: Construct the square matrix.

$$\tilde{r}_{ij} = \frac{i}{r_{ij}} ; i, j \in \{1, \ldots, n\}$$

Equation (10) was used to formulate the positive and negative elements of the decision matrix. After that, the decision matrix was normalized by equation (7). Lastly, a square matrix was made using equation (11).

$$s_j = \max_i r_{ij} = s_{kj} ; i, j \in \{1, \ldots, n\}$$

Here, $s_{kj}$ states the maximum number of the $jth$ criteria, which were taken from the decision matrix with $k_i$ rows to formulate the square matrix and $s_j = s_{kj}$ and $s_j = s_j$ [39].

### Step 5: Estimate the relative impact loss matrix with respect to the values obtained from the previous step.

$$p_{ij} = \frac{s_{ij} - s_{ij}}{s_{ij}} \quad (p_{ij} = 0, i, j = 1, 2, 3, \ldots, m)$$

where, $p_{ij}$ is the relative impact loss of the $jth$ criterion.

### Step 6: Develop the weight system matrix.

$$A = \begin{bmatrix} -\frac{\sum_{i=1}^{n} P_{i1}}{n} & P_{12} & \cdots & P_{1n} \\ \vdots & \vdots & \ddots & \vdots \\ P_{n1} & P_{n2} & \cdots & -\frac{\sum_{i=1}^{n} P_{in}}{n} \end{bmatrix}_{n \times n}$$

### Step 7: Calculate the criterion impact loss weight.

We first solved the linear system of equations as follows:

$$AX = 0$$

### Table 2

Linguistic expressions and their consequent triangular fuzzy numbers.

| Triangular fuzzy numbers     | Equally important (EI) | Weakly important (WI) | Fairly Important (FI) | Very important (VI) | Absolutely important (AI) |
|-----------------------------|------------------------|-----------------------|----------------------|---------------------|--------------------------|
| \((1, 1, 1)\)               | \((2/3, 1, 3/2)\)      | \((3/2, 2, 5/2)\)    | \((5/2, 3, 7/2)\)   | \((7/2, 4, 9/2)\)  | \((7/2, 4, 9/2)\)       |

### Table 3

Values of FCI.

| $\hat{df}_{av}$ | (1.1, 1) | (2/3, 1.3/2) | (3/2, 2.5/2) | (5/2, 3.7/2) | (7/2, 4.9/2) | (9/2, 5.11/2) | (11/2, 6.13/2) | (13/2, 7.15/2) | (15/2, 8.17/2) | (17/2, 9.19/2) |
|------------------|----------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|
| $\hat{df}_{c}$  | (0, 0)   | (0.0, 1.36)  | (0.34, 44.216) | (0.71, 1.429) | (1.31, 1.63, 5.69) | (1.96, 2.30, 7.04) | (2.65, 3.835) | (3.36, 3.73, 9.64) | (4.09, 4.47, 10.91) | (4.85, 5.23, 12.15) |
\[
\begin{bmatrix}
-6.76 & 1.00 & 0.80 & 0.67 & 0.97 \\
0.98 & -5.84 & 0.70 & 0.56 & 0.50 \\
0.99 & 0.98 & -3.55 & 0.00 & 0.95 \\
0.99 & 0.98 & 0.00 & -3.28 & 0.95 \\
0.95 & 0.95 & 0.60 & 0.69 & -5.77 \\
\end{bmatrix}
\begin{bmatrix}
x_1 \\
x_2 \\
x_3 \\
x_4 \\
x_5 \\
\end{bmatrix} = 0
\]  
(15)

The criterion Impact Loss Weight is \( x \) and the vector \( X \) containing the elements \( (x_1, \ldots, x_5) \) is the solution of this system \( < \) which can be resolved mathematically as follows.

\[
X = A^{-1}B
\]  
(16)

where \( B \) is a nonzero vector near vector \( 0 \) used to determine the nonzero solution as shown below:

\[
B = [-2.82E-17 \ 0 \ 0 \ 0 \ 0]^T
\]  
(17)

In the end, the weights of the criteria were estimated by the CILOS method as follows:

\[
X = \begin{bmatrix} 0.154 & 0.169 & 0.169 & 0.338 & 0.169 \end{bmatrix}^T
\]

**Step 8**: Calculate the Integrated Determination of Objective Criteria Weights considering the entropy weight \( (W) \) and CILOS weight \( (x) \).

\[
\omega_j = \frac{x_j W_j}{\sum_{j=1}^{n} x_j W_j}
\]  
(18)

### 2.5. Aggregated Weighting Method

To obtain more reliable and consistent weight, we implemented the following aggregated formula, which is a combination of the OF-BWM and IDOCRIW methods [39].

\[
w_{\text{Aggregated}} = \Delta w_{\text{OF-BWM}} + (1 - \Delta) w_{\text{IDOCRIW}}
\]  
(19)

where \( \Delta \) is the contribution factor and its suggested range is from 0 to 1. Here, \( \Delta = 0.5 \) was considered.

### 2.6. CoCoSo under different normalization methods

**Step 1**: Construct the decision matrix \( x_{ij} \)

\[
x_{ij} = \begin{bmatrix}
x_{i11} & x_{i12} & \cdots & x_{i1n} \\
x_{i21} & x_{i22} & \cdots & x_{i2n} \\
\vdots & \vdots & \ddots & \vdots \\
x_{im1} & x_{im2} & \cdots & x_{imn} \\
\end{bmatrix}
\]  
(20)

Here, \( m \) is the number of off-grid and on-grid energy system alternatives, \( n \) is the number of assessment criteria and \( x_{ij} \) is the performance of the \( i^{th} \) alternative with respect to the \( j^{th} \) criterion.

**Step 16**: Normalize the decision matrix based on the following normalization methods [40].

**N1**: Max-Min linear normalization (used in original CoCoSo):

\[
n_{ij} (\text{Beneficial Criteria}) = \frac{x_{ij} - \min x_{ij}}{\max x_{ij} - \min x_{ij}}
\]  
(21)

**N2**: Linear Max normalization:

\[
n_{ij} (\text{Beneficial Criteria}) = \frac{x_{ij}}{\max x_{ij}}
\]  
(22)

**N3**: Linear Sum normalization:

\[
n_{ij} (\text{Beneficial Criteria}) = \frac{1}{\sum_{j=1}^{m} x_{ij}}
\]  
(23)

**N4**: Vector normalization:

\[
n_{ij} (\text{Beneficial Criteria}) = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{m} x_{ij}^2}}
\]  
(24)

**N5**: Logarithmic normalization:

\[
n_{ij} (\text{Beneficial Criteria}) = \ln \frac{x_{ij}}{\ln\left(\prod_{j=1}^{m} x_{ij}\right)}
\]  
(25)

Step 17: Calculate the values of \( S_i \) for each normalization method, which are derived from the grey relational generation technique.

\[
S_i = \sum_{j=1}^{n} \left(w_j n_{ij}\right)
\]  
(26)

The values of \( w_j \) are obtained from equations (6), (18) and (19).

Step 18: Calculate the values of \( P_i \) for each normalization method and each weighting method, which are obtained based on the WASPAS multiplicative attitude.

\[
P_i = \sum_{j=1}^{n} (n_{ij})^{w_j}
\]  
(27)

Step 19: Determine the aggregated appraisal score for each normalization method.

\[
k_{ia} = \frac{P_i + S_i}{\sum_{i=1}^{l} (P_i + S_i)}
\]  
(28)
\[ k_{ib} = \frac{S_i}{\min S_i} + \frac{P_i}{\min P_i} \]  
\[ k_{ic} = \frac{\lambda(S_i) + (1 - \lambda)(P_i)}{\max S_i + (1 - \lambda)\max P_i} \]

Equation (33) demonstrates the arithmetic mean of sums of the WSM and WPM scores, equation (34) expresses a sum of relative scores of WSM and WPM and equation (35) shows the balanced compromise of the WSM and WPM model scores [28]. In this study, the value of \( \lambda = 0.50 \).

Step 20: Calculate the final appraisal scores for each energy system using each normalization method.

\[ k_i = (k_{ia}k_{ib}k_{ic})^\frac{1}{3} + \frac{1}{3}(k_{ia} + k_{ib} + k_{ic}) \]  

3. Results

3.1. Selection of the criteria

After selecting the list of criteria, we implemented the Delphi process. Table 4 reveals that the value of Coefficient of Variance (CV) of each criterion is less than 0.50, which satisfies the condition of Step 3 and the Delphi process stops. However, to check the consistency among the experts, we estimated modified Kappa (\( K' \)) using equation (1). This study brought together 6 experts from multidisciplinary backgrounds as one panel and asked each expert to rate the criteria on a Likert-scale of 1–5 (Strongly Disagree-Strongly Agree). Table 5 shows the experts’ ratings and the obtained modified Kappa (\( K' \)) values. The table shows that for all criteria \( K' > 0.74 \), which signifies ‘Excellent’ interpretation among experts. Finally, the findings confirmed five criteria.

3.2. wt of the criteria

First, we estimated the weights of the five criteria through FO-BWM and the expert panel chose ‘OLF’ as the ‘Best’ criterion and ‘COE’ as the ‘Worst’ criterion. Then, we solved equation (2) using the optimization software GAMS (General Algebraic Modeling System) to derive optimal fuzzy weights of the five criteria. The obtained fuzzy weights of the criteria were EB(\( w_1^* \)) = (0.083, 0.116, 0.116), OLF(\( w_2^* \)) = (0.491, 0.491, 0.524), PIT(\( w_3^* \)) = (0.210, 0.210, 0.210), PSR(\( w_4^* \)) = (0.150, 0.150, 0.150) and COE(\( w_5^* \)) = (0.033, 0.033, 0.033). The optimal objective value \( \beta^* \) was estimated at 0.626 and the estimated fuzzy FCR was (0.109, 0.063, 0.015). To check the consistency of experts’ opinions, we calculated the value of R (FCR), where R (FCR) = 0.061. The obtained R (FCR) = 0.061 ≤ 0.10, thus satisfying the condition and proving that experts were consistent regarding their decisions. Finally, we used equation (6) to defuzzify the fuzzy numbers and to get the crisp weights of the criteria. Fig. 2 represents the final weights of the criteria. The obtained criteria weights were Environmental Benefit (EB) = 10.5%, Opportunity of Local Funding (OLF) = 50.2%, Project Implementation Time (PIT) = 21%, Power Supply Reliability (PSR) = 15% and Cost of Energy (COE) = 3.3%. The OF-BWM was based on expert ratings, which were subjective in nature. Therefore, to avoid biasness, we implemented an objective weighting method called IDOCRiW. After calculating the weights of the entropy and CILOS, we calculated the IDOCRiW weight of the criteria using equation (18). Fig. 2 shows that the weights of COE, PIT, OLF, PSR and EB are 33.6%, 11.9%, 15.9%, 27.3% and 11.2%, respectively. The deviation of results between these two methods raised new concern. Therefore, this study aggregated the OF-BWM and IDOCRiW methods to get more reliable and valid results. The aggregated weights of the criteria were obtained from equation (19). Fig. 2 demonstrates that OLF obtained the highest weight of 32.95% and EB obtained the lowest weight of 10.60%, where COE, PIT and PSR obtained 18.46%, 16.45% and 21.15%, respectively. The figure shows that the Aggregated Weighting Method gives balanced results compared with OF-BWM and IDOCRiW. Table 6 shows that OF-BWM and IDOCRiW have a weak relationship as both of them are negatively correlated, which points to the opposing characteristics of subjective and objective weighting methods. On the other hand, the correlation of the aggregated method shows a strong relationship between the OF-BWM and IDOCRiW methods, as both of them are positively correlated. However, the relationships among them are not the strongest as the Pearson correlation value is less than 1.

3.3. Ranking of the energy systems

Using equations 21–30, this study used each normalization method to normalize the decision matrix. Then, using equation (31), we calculated the \( S_i \) for each normalization method by putting the weights in that equation obtained by the OF-BWM, IDOCRiW and the Aggregated Weighting Method. Similarly, using equation (32), we estimated the values of \( P_i \) for each normalization method. Finally, we calculated appraisal scores for each energy system, using equation (36), by applying each normalization method. Considering the five (5) normalization methods and three (3) weighting methods, the simulation generated a total of fifteen (15) models which rank the energy systems. Fig. 3 shows the following ranking of the first 5 models: SHS > Mini-Grid > Solar Park > Wind > Coal. The ranking demonstrates that all energy systems get the same rank using the weight of OFBWM under the 5 normalization methods. These models also demonstrate that the CoCoSo method is adaptable with all these normalization methods, when weights were obtained from OF-BWM. Fig. 4 gives the ranking results of M6-M10, showing that M6 and M7 provide the same ranking, i.e., Mini-Grid > SHS > Solar Park > Wind > Coal, which is slightly different from M1-M5. On the other hand, M9 and M10 provide the same rankings as M1-M5. However, M8 gives a different ranking scenario, i.e., SHS > Mini-Grid > Solar Park > Coal > Wind, where fossil fuel based power generation using coal is prioritized over renewable power. Here M6 and M7 are abatable with N1 and N2, while M9 and M10 are adaptable with N4 and N5. On the other hand, M8 is adaptable with N3. Fig. 5 shows the rankings of M11-M15. As seen in the figure, except for M15, all models give different rankings. Model 15 gives the same ranking as M1-M5 and M9-M10. The model is adaptable only with N5, while other normalization methods are not well adapted with M11-M14.

3.4. Integrated ranking

The majority of the models demonstrated that SHS is the best

| List of criteria          | Unit | Attributes | CV  |
|---------------------------|------|------------|-----|
| Environmental Benefit (EB)| Ordinal | Positive (+) | 0.21 |
| Opportunity of Local Funding (OLF)| Ordinal | Negative (−) | 0.20 |
| Project Implementation Time (PIT)| Ordinal | Negative (−) | 0.26 |
| Power Supply Reliability (PSR)| Ordinal | Positive (+) | 0.31 |
| Cost of Energy (COE)| USD/KWh | Negative (−) | 0.19 |
energy system. However, some models prioritizing Mini-Grids as the ranking models work differently with different normalization and weighting methods. It is also observable that all models prioritize clean energy systems, except for one model, which also creates a dilemma regarding the final decision. Fig. 6 shows the ranking of all 15 models. To get rid of this dilemma, integrated ranking of these 15 models is necessary to choose the best models with the best solution.

### Table 5
Agreement of decision makers (DM).

| List of criteria | DM 1 | DM 2 | DM 3 | DM 4 | DM 5 | DM 6 | \( k' \) | Interpretation |
|------------------|------|------|------|------|------|------|---------|---------------|
| EB               | 4    | 4    | 4    | 3    | 4    | 3    | 1       | Excellent     |
| OLF              | 4    | 3    | 3    | 2    | 3    | 3    | 0.830   | Excellent     |
| PIT              | 3    | 4    | 3    | 3    | 2    | 4    | 0.830   | Excellent     |
| PSR              | 3    | 4    | 3    | 3    | 1    | 4    | 4       | Excellent     |
| COE              | 2    | 3    | 4    | 3    | 3    | 4    | 0.830   | Excellent     |

**Fig. 2.** Weights of the criteria.

**Fig. 3.** Ranking of energy systems from M1-M5.

**Fig. 4.** Ranking of energy systems from M6-M10.

**Fig. 5.** Ranking of energy systems from M11-M15.

### Table 6
Correlation among the weighting methods.

|          | OF-BWM | IDOCRiW | Aggregated |
|----------|--------|---------|------------|
| OF-BWM   | 1      | −0.30   | 0.50       |
| IDOCRiW  | 1      | 1       | 0.60       |
| Aggregated | 1      |         | 1          |

**Fig. 6.** Ranking of all 15 models.
This study implemented three (3) methods to obtain the best ranking scenario, including the grade average method, Borda method [41], and Copeland method [42]. The grade average method is the mean of the rankings obtained from the 15 models. In this method, the smallest value is considered as the best alternative. The Borda method is a pairwise comparison method, where if the value of the grade average of an alternative is greater than that of the other alternative, then the value 1 is assigned, or else 0 is allocated to the associated matrix elements (Table 7). After creating the pairwise comparison matrix, we calculated the row sum for each alternative d based on the values obtained using the Borda method. We estimated the value of the Copeland method by subtracting the row sum values from the column sum values of Table 7. It should also be noted that the values obtained for the energy systems from the Borda and Copeland methods are ranked from descending to ascending order, which means the highest value is considered as the best energy system. Fig. 7 shows the final results of these three methods. The rankings obtained from the grade average, Borda, and Copeland methods are SHS (1.40), Mini-Grid (1.67), Solar Park (3)>Wind (4.33)>Coal (4.60); SHS (4)>Mini-Grid (3)>Solar Park (2)>Wind (1)>Coal (0) and SHS (4)>Mini-Grid (2)>Solar Park (0)>Wind (2)>Coal (4), respectively. All of these rankings support M1-M5, M9, M10 and M15, which are considered as the best fitted models. However, sensitivity analysis is required for further verification of these eight (8) models.

3.5. Sensitivity analysis

This study carried out two types of sensitivity analysis to explore the stability of the modeling and the relative input-output model behavior [43]. Sub-section 3.5.1 shows the influence of the λ value on the final ranking and sub-section 3.5.2 analyzes the effect of change in criteria weights.

3.5.1. Influence of the λ value on the final ranking

In proposed approach considered the λ value to be 0.50. To check the stability of the ranking order of the energy systems of M1-M5, M9, M10 and M15, we varied the values of λ from 0 to 1. Fig. 8 demonstrates that the value of the final appraisal score (k1) varies, when the value of λ is changed. All of these figures show that the rank orders of the energy systems are stable with respect to all 8 models, which justifies SHS > Mini-Grid > Solar Park > Wind > Coal. Except for slight variation of the best energy system, SHS, in M1 and M2, the other models show excellent stability in ranking SHS. Overall, M5, M10 and M15 show better stability in ranking with respect to all alternatives compared to the other models.

3.5.2. Effect of change in the independent weights of the criteria

The previous SA proved the utility of M5, M10, and M15. To prove its overall effectiveness, this study created a total of 16 scenarios (including the original weight) from each weighting method and varied to 30%, 40% and 50%. Figs. 9–11 show that the rankings of the energy systems are stable and SHS and Mini-Grid are the best for off-grid areas if the impact of the pandemic lasts a long time. However, M5 and M10 demonstrate that OLF (C3) will be an important criterion for Bangladesh that will strongly influence the decision making when choosing between these two off-grid energy systems. On the other hand, M15 shows that all criteria will play almost equal roles with respect to the energy system alternatives during the decision making process.

The 1st sensitivity analysis has demonstrated the robustness of the proposed 8 models as they provide the same ranking order. However, based on changes of the final appraisal score of the CoCoSo method with respect to λ, it is seen that logarithmic normalization (N5) is the most suitable with OF-BWM, IDOCRIW, and the Aggregated Weighting methods as they show the maximum stability of the alternatives compared to the other normalization methods. This is also in line with the 2nd selectivity analysis, which showed that the stability of the three models (M5, M10, and M15) did not obviously change. Additionally, if the decision matrix has smaller dimensions and fewer alternatives, the logarithmic normalization method is an excellent choice to solve the problem [44]. This finding was also confirmed by the CoCoSo method in this study.

4. Discussion

The final results from 8 models demonstrate that SHS and Mini-Grid systems need to be prioritized among all options. The sensitivity analysis further shows that OLF is the key criterion and will influence the off-grid energy systems if the pandemic continues for a long time. Presently, the COVID-19 pandemic has significantly affected the economies of developing countries like Bangladesh, and it is expected that the country will need to depend on local

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**Table 7**

|                   | Mini-Grid | SHS | Coal | Solar Park | Wind |
|-------------------|-----------|-----|------|------------|------|
| Mini-Grid         | 0         | 0   | 1    | 1          | 1    |
| SHS               | 1         | 0   | 1    | 1          | 1    |
| Coal              | 0         | 0   | 0    | 0          | 0    |
| Solar Park        | 0         | 0   | 1    | 0          | 1    |
| Wind              | 0         | 0   | 1    | 0          | 0    |

**Fig. 6.** Ranking of all 15 models.

**Fig. 7.** Results obtained from the grade average, Borda and Copeland methods.
Fig. 8. Sensitivity analysis of M1-M5, M9, M10, and M15.
funding in the future rather than foreign investment. Also, urgent local funding is necessary to establish power supply as soon as possible with stable system reliability and sustainability, so that emergency situations can be handled in the future.

Off-grid renewable energy provides reliable, pollution free, clean and affordable power for the local people. Thus, these kinds of energy are essential in the instant response to the COVID-19 pandemic. Additionally, renewable energy systems help to recover from economic crises, reduce carbon emissions, guarantee energy security, create new jobs, strengthen social bonding and contribute to protecting local people’s health and life, which will help Bangladesh to recover from the pandemic situation in the future.

The result also shows that under the long term impact of the pandemic, SHS and Mini-Grid are prioritized over grid connected Solar Park and Wind systems, as they can contribute to electrifying the rural off-grid areas of Bangladesh with low investment cost. Moreover, off-grid energy systems can quickly deal with the emergency situation (e.g. electrifying rural hospitals) as they do not need to be connected with the grid through complex technical procedures. Generally, SHSs are reliable, sustainable, quick and easy to install, and can help the local people to recover from power shortages during the pandemic under lockdown situations. The results obtained from this study also show that Mini-Grids also provide a safe option during lockdown periods, which allow consumers to get reliable electricity from stakeholders without concern for the technical difficulties.

A study has demonstrated that SHSs are a better option than Mini-Grids based on a case study in Bangladesh [45], which is also in line with this study. It is worth noting that off-grid systems can be grid connected only when the length of the grid line is less than the critical distance from the off-grid energy system [46]. Particularly, in southern areas of Bangladesh, e.g. the Char areas, which are far from the nearest sub-station, connecting to the grid is difficult. A recent review based study also suggested using SHSs and Mini-Grids in the future if another pandemic like COVID-19 occurs [47]. This study has confirmed the quantitative feasibility of implementing these two types of off-grid energy systems in the future.

At present, it is critical for GoB to plan future large scale grid connected solar parks and wind energy projects, as local fund management is difficult for the country due to the high investment cost. The pandemic has also created the risk large scale renewable energy projects being dropped in developing countries as governments initiate incentive packages to promote local investments and local businesses to stimulate the internal economy [48]. Therefore, it is necessary to find external funding from foreign donor agencies. However, even developed countries are badly affected by the pandemic, and global physical communication has been blocked, resulting into obstacles to collecting foreign funding from developed countries and getting technical help from foreign experts. Moreover, solar park projects require 145.2 square feet/KW, which is a big challenge for the off-grid areas of Bangladesh as there is severe land scarcity in the country [49]. On the other hand, the risk of wind turbine projects is high and may lead to failure as Bangladesh is frequently hit by cyclones. In this context, the results also suggest that solar parks and wind energy systems are the 3rd and 4th ranked priorities for future planning as they are more environmentally beneficial and more likely to be supported by local funds compared with fossil fuel (coal) based energy. Moreover, in 2020, the global energy demand of coal dropped by −7.73%, which is the lowest when compared with other fossil fuels. Meanwhile,
renewable energy had the highest positive growth at 0.79% [50]. This implies that in the future, if the COVID-19 pandemic extends for a long time, the energy demand from fossil fuel based energy systems will decrease and the energy demand from renewables will increase. Such a finding justifies the importance of this study, as the results show that renewable energy will be prioritized in Bangladesh. It is important to note that the reliability of the grid connected system is questionable since the power failure of the system may cause a complete blackout. On the other hand, an off-grid energy system can store electricity in batteries and can be used when necessary, particularly during a lockdown period. Therefore, SHS and mini-grid based off-grid energy systems can be promoted in the future, considering the long-term effects of the COVID-19 pandemic in Bangladesh.

Because long-term pandemic funding from foreign agencies can be unpredictable and time-consuming, this study suggests increasing local funding sources through various local NGOs and IDCOL to build SHS and mini-grids. For example, IDCOL’s basic subsidy package in Bangladesh provides a 76% subsidy ratio to mini-grid developers, and the package includes a capital grant of up to 50% of project costs and a concessional loan of up to 30% of project costs. If mini-grid developers are unable to take advantage of this subsidy package, they will be forced to finance their capital expenditures with commercial or foreign loans. With current commercial loan interest rates in Bangladesh and a 5-year loan term, this kind of project’s net present value would be more than four times higher than it would be without IDCOL subsidies. In this context, a transparent and consistent subsidy scheme is required, which could be beneficial because most mini-grid initiatives require initial funding. In order to promote greater social empowerment during this pandemic, the GOB may also grant specific tariff subsidies for farming, livelihood enhancement, and small cottage industries.

As the global vaccination rate rises, developing countries will require more vaccines. However, it is critical to not only increase the amount of vaccines available, but also to ensure that they are distributed equally in rural and urban areas. Because of storage issues, regular vaccination is sometimes interrupted in rural and off-grid areas. This is challenging as most COVID-19 vaccines require a refrigerator temperature range of 2 °C–8 °C. SHS and mini-grid systems are capable of assisting in this area by providing the electricity supply to refrigerators. SHS, in particular, can provide fast assistance in the event of an emergency. Moreover, temporary clinics can be established and powered by off-grid energy systems (SHS and mini-grid) in rural isolated areas of Bangladesh to deal with serious COVID-19 patients. For example, SHS was successfully built in rural clinics in Nigeria, Kenya, and Afghanistan, providing reliable energy for necessary surgery and necessary equipment for COVID-19 patients, including ventilators, defibrillators, centrifuges, and patient monitoring systems [51,52]. This lesson can be implemented for Bangladesh and other developing countries.

5. Conclusion and policy implications

5.1. Conclusion

The COVID-19 pandemic has worsened the dilemma of whether to extend the existing grid or adopt off-grid energy systems in the off-grid areas of developing countries. This study proposed an integrated MCDM approach proposed that has been shown to be effective using two types of sensitivity analysis to address the decision dilemma of ranking and selection of energy systems in the scenario of a long-lasting pandemic. Based on the case study of Bangladesh, this study draws the following conclusions.

- After the Delphi process, a total of five criteria were selected. The values of the CV of all criteria were less than 0.50. Additionally, all the experts shared strong agreement regarding the selection of the criteria.
- After evaluating OF-BWM, the best criterion was Opportunity of Local Funding (OLF) at 50.2%, and the worst criterion was Cost of Energy (COE), having a weight of 3.3%. The obtained weights of COE, PIT, OLF, PSR and EB from the IDOCRiW method are 11.9%, 15.5%, 27.3% and 11.2%, respectively. Similarly, results of the same criteria obtained from the OF-BWM integrated IDOCRiW method are 18.46%, 16.45%, 32.95%, 21.15% and 10.60%, respectively.
- After evaluating the 15 models through 3 integrated ranking approaches (Grade Average, Borda and Copeland), it was found that 8 models are feasible and provide the same ranking with the different values of the energy systems. The ranking obtained from the integrated approach is SHS > Mini-Grid > Solar Park > Wind > Coal.
- SHS and Mini-Grids are the best alternatives in off-grid areas, followed by large scale solar parks, wind and coal to deal with the COVID-19 pandemic in the future.
- Opportunity of Local Funding (OLF) will be an important criterion under a long-term pandemic, which will influence decision making when choosing between SHS and Mini-Grids.
- Sensitivity analysis concludes that the rankings obtained from the 8 models are stable and valid when the CoCoSo model parameter λ is varied. Both sensitivity analyses also demonstrate that CoCoSo is highly stable with logarithmic normalization in the decision matrix used in this study.

The major limitation of this study is the small dimension of the decision matrix. Therefore, more criteria and alternatives can be considered in the future. Different off-grid and on-grid energy systems can also be further designed using optimization tools and the MCDM method can then be used to ease the dilemmas of energy planning in off-grid areas in developing countries.

5.2. Policy implications

This study makes the following recommendations for the development of a country’s clean energy expansion during the COVID-19 pandemic, which will not only improve comprehension of the selection process but also provide useful policy and practice insights.

- In a long-term pandemic scenario, funding from foreign agencies can be unpredictable and time-consuming. This study suggests increasing local funding sources through various local NGOs, credit unions, and IDCOL to build SHS and mini-grids.
- Analysis also shows that Power Supply Reliability (PSR) is also one of the important factors that influence the decision-making process. SHS and mini-grid systems should be implemented in off-grid locations where grid extension is unlikely in the near future. If the rate of COVID-19 rises in a particular off-grid area, lockdown or self-isolation may be required. In this regard, residential load demand would increase while industrial load demand decreases. SHS and mini-grid systems can meet this demand because they provide reliable power supply for residential loads.
- Massive vaccination is challenging for off-grid areas as most COVID-19 vaccines require a refrigerator temperature range of 2 °C–8 °C. SHS and mini-grid systems are capable of assisting in such areas by providing electricity supply to refrigerators.

The proposed model requires the involvement of all levels of...
people from strategic, tactical, and operational levels, as the effectiveness of the proposed strategy is reliant on expert judgment. Therefore, the proposed integrated MCDM has demonstrated its utility as an effective tool to achieve resilient energy planning in developing countries, considering the future impact of pandemics like COVID-19.

Credit authorship contribution statement

Taufis Ali: Conceptualization, Methodology, Software, Data curation, Writing – original draft. Kamaledin Aghaloo: Investigation, Writing – review & editing, Project administration. Yeu-Ru Chiu: Supervision, Writing – review & editing. Munir Ahmad: Writing – review & 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.

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