International Journal of Applied Optimization Studies
IJAOS
İSÜ İSTİNYE ÜNİVERSİTESİ İSTANBUL

# A Bio-Inspired Approach Enabled Group Decision Meetings Facilitation

Abdelkader Ould Mahraz[1], Bakhta Nachet[2], Abdelkader Adla[2,*]

[1]Computer science department, University of Ghardaia, Ghardaia, Algeria
[2]Computer science department, University of Oran 1 Ahmed Ben Bella, Algeria
*E-mail (corresponding author): adla.abdelkader@univ-oran1.dz

**ABSTRACT**

Group decision meetings consume a great deal of time and effort in organizations. Group Decision Support Systems (GDSS) provide computational support to group decision-makers to support these processes. However, most of them are perceived to be extremely unproductive in terms of efficiently utilizing the participants' time and effectively achieving the group decision-meeting objectives. These shortcomings occur frequently because effective guidelines or procedures are not used. To overcome these problems, GDSS would benefit from embedding some facilitation techniques and integrating a human facilitator who guides the group members through the decision-making process. This article proposes a framework for group facilitation that supports facilitators based on a model of the decision-making process where group facilitation tasks are automated, at least partially, increasing the ability of a facilitator to monitor and control the group decision-meeting process. We consider decision support approaches such as bio-inspired optimization methods that potentially offer these capabilities and assist the facilitator and decision-makers. We use the Elephant Herding Optimization (EHO) method to develop the system, and its evaluation is mainly based on the Analytic Hierarchy Process. We experiment with our approach with the breakdown diagnosis application in a complex industrial system. The results demonstrate the feasibility and effectiveness of our proposal.

**Paper type:** *Research Article*

*Received 2023-12-19*
*Revised 2023-03-27*
*Accepted 2024-04-05*

**Keywords:**
*Group decision-making; Group decision support systems; Group facilitation; Bio-inspired optimization methods; EHO algorithm.*

## 1. Introduction

The performance of groups interacting with Group Decision Support Systems (GDSS) has been at the heart of the issues raised in numerous studies (Carneiro, 2021) (Shim et al., 2002). GDSS does not address areas of group functioning, such as decision-meeting design or managing verbal communications (Adam, 2012). These and other facilitation activities must come from people who have a great interest in the facilitator.

The integration of good computer tools with effective human facilitation can lead to a more effective meeting than by itself (Mahraz et al., 2016). Many group facilitation tasks can be automated, at least partially, to increase the bandwidth of group communication and the ability of the facilitator to monitor and control the group decision process. An effective system would reduce the need for developing technical competence and would make any individual who so desired an effective facilitator in aiding the group members. An automated process to aid the facilitator must include tools to monitor group and individual behaviors, indicators to know when to offer or integrate information, as well as know when to employ particular techniques to move the group towards congruence (Adla, 2010; Adla et al., 2011).

In this article, we consider a framework for group facilitation that supports facilitators by automating group facilitation tasks, at least partially, to increase the ability of a facilitator to monitor and control the group decision process. Bio-inspired optimization methods potentially offer these capabilities and can assist the facilitator and decision-makers along with the group decision-making processes. In particular, we use the EHO-based method combined with the Analytic Hierarchy Process mainly in the evaluation stage.

The remainder of this paper is as follows: Section 2 presents Artificial Intelligence methods to support group decision-making. In section 3 we describe our approach to support group decision-making based on bio-inspired method, namely the EHO algorithm. An example of an application and the implementation of a prototype to illustrate the feasibility of our proposal are presented in section 4. Finally, some conclusions and suggestions for future work are provided in section 5.

## 2. Artificial intelligence methods to support group decision-making

With the rise of artificial intelligence, decision-making methods enclose three categories of strategic decision-making approaches: multi-attribute decision-making methods, mathematical programming methods and AI methods (Rahman & De Frei, 2009). The latter uses several artificial intelligence techniques to assist in the decision-making process. These techniques provide tools to solve real-world problems with large amounts of data. Due to their capabilities (Understanding the situation and making sense of the uncertainty or ambiguity), they learn through experience, react promptly to a new or adaptive situation, and Handle perplexing solutions. Using knowledge to recognize various factors in a decision), they make intelligent support for group decision-making (Parneersel-Vam, 2020). Intelligent decision-making has been growing and emerging as powerful tools by using various AI techniques such as Artificial neural networks (ANN) (Mumali, 2022), Fuzzy logic (FL) (Wu & Xu, 2020), and Bio-inspired algorithms (Darwish, 2018). Bio-inspired algorithms are revolutionary techniques for solving hard and complex problems. They aimed to find the optimal solution to problems while maintaining perfect balance among its components, from a search space at a quicker rate for a given optimization problem compared to some of the existing conventional search algorithms that take longer to converge. Bio-inspired algorithms possess the following capabilities: Applicable to a wide range of problems, have few control parameters to tune the algorithm and have a better convergence rate while reaching the optimum value (Fan et al., 2020).

Elephant herding optimization (EHO) (Ismael, 2019) (Wang et al., 2016) is a nature-inspired metaheuristic optimization algorithm based on the herding behavior of elephants. EHO uses a clan operator to update the distance of the elephants in each clan with respect to the position of a matriarch elephant. Various aspects of the EHO variants for continuous, combinatorial, constrained, and multi-objective optimization are reviewed. The EHO method is superior to several state-of-the-art metaheuristic algorithms, which have been demonstrated for many benchmark problems and in various application areas. EHO algorithm can find much better solutions to most benchmark problems than three other algorithms (Biogeography-Based Optimization (BBO) (Zheng, 2019) and Genetic Algorithms (GA) (Yang, 2021). Based on the experimental results, researchers concluded that EHO has good characteristics as an optimization algorithm and performs better than the PSO algorithm (Gad, 2022) used for comparison.

To our knowledge, no work using bioinspired EHO algorithms in the literature related to DSS or GDSS exists. Thus, we present a new approach to facilitate the group decision-making process using the EHO algorithm (Solutions organization, evaluation of alternatives, and Solution selection).

## 3. The proposed approach

In group decision-making, alternatives amongst which a decision must be made can range from a few to a few thousand; the decision-makers need to narrow the possibilities down to a reasonable number and sort alternatives. The alternatives proposed by the decision-makers may be:

- Redundant: the alternatives are syntactically identical;
- Synonyms: the alternatives are syntactically different but semantically identical;
- Conflicting: two contradictory or conflicting alternatives mean that the application of one is incompatible with the application of the other;
- Generic: an alternative may be more general than another. In this case, the application of the most general includes the application of the most specific;

These alternatives must be screened and sorted before being evaluated, thus enabling decision-making. The alternative screening and sorting tool contributes to retrieving and removing all the redundant, conflicting and synonymous decisions. The screening and sorting tool identifies semantic relationships between decisions and then presents them to the decision-makers, who will have the duty to decide among the suggested alternatives that will be removed and which have to be kept based on their expertise.

Our work aims to integrate an optimization tool based on EHO algorithm to facilitate group decision-making process screening and sorting tool (see within a Group Decision Support System (GDSS).

### *3.1. Elephant herding optimization algorithm*

The elephant herding optimization (EHO) algorithm is a recent bio-inspired meta-heuristic algorithm proposed in (Ismael, 2019) (Wang et al., 2016). This search algorithm is invented by simulating elephant herds' biological behaviors. In nature, the elephant is considered a social animal, and the herding consists of several clans of female elephants and their calves. Each clan moves under the influence of a matriarch or a leader elephant. The female elephants live with their family groups, while the male elephants separate when they grow up and live in contact with their family group using low-frequency vibrations. Based on these biological behaviors, an algorithm for the male elephant focuses on global exploration, and the female elephant (matriarch) focuses on local intensification.

EHO solves all kinds of global optimization problems and the herding behavior of the elephants can be modeled as follows:

1) Each population is composed of some clans at the same time, and each clan has a fixed number of elephants.
2) At each generation, a fixed number of males will leave their family group and live far away.
3) The elephants live together in each clan under a leader called a matriarch.

The herding behavior is mathematically decomposed into two types of operators: one is an updating operator and another is a separating operator. The algorithm is mathematically modeled and is given by

**Algorithm** 01 Pseudo code of EHO

1. ***Initialization****: Initialize the generation counter g=1; the maximum generation MaxGen and the population;*
2. ***While*** *g<MaxGen* ***do***
3. *All the elephants should be classified according to fitness*
4. *Perform clan updating operator*
5. *Perform separating operator*
6. *Assess the population by newly updated positions*
7. *g:=g+1*
8. ***end while***

Where updating operator is given by

**Algorithm** 02 Pseudo code of clan updating operator

***for*** *ci=1 to nClan (for all clans in elephant population)* ***do***
  ***for*** *j=1 to* $n_{ci}$ *(for all elephants in clan ci)* ***do***
    *Update* $x_{ci,j}$ *and generate xnew,ci,j by Eq. (1).*
    ***if*** $x_{ci,j}=x_{best,ci}$ ***then***
      *Update* $x_{ci,j}$ *and generate* $x_{new,ci,j}$ *by Eq. (2).*
    ***end if***
  ***end for*** *j*
***end for*** *ci*

$$x_{new,ci,j} = x_{ci,j} + \alpha\left(x_{best,ci} - x_{ci,j}\right) * r \tag{1}$$

$$x_{new,ci,j} = \beta * x_{center,ci} \tag{2}$$

$$x_{center,ci,j} = \frac{1}{n_{ci}} * \sum_{j=1}^{n_{ci}} x_{ci,j,d} \tag{3}$$

The separating operator is given by

**Algorithm** 03 Pseudo code of separating operator

***for*** *ci=1 to nClan (all the clans in elephant population) do*
  *Replace the worst elephant in clan ci by Eq. (4).*
***end for*** *ci*

$$x_{wort,ci} = x_{min} + (x_{max} - x_{min} + 1) * rand \tag{4}$$

### *3.2. Applying EHO algorithm to support group decision-making*

The principle of the transition from the group decision-making context to the artificial model is as follows (Figure 1):

1) One elephant represents each alternative expressed by the decision-maker
2) Each clan obtained after classification represents a class of ideas considered as homogeneous.

### *3.3. Model development*

This model concerns the second phase (learning during supervised classification), which aims to find the proper values of $\varepsilon_1$, $\varepsilon_2$ and $\varepsilon_3$ that validate the model. For each parameter ($\varepsilon_i$) we get a class (Sol. Opti), which will be used in the next phase (Alternative's selector phase), as shown in Figure 2.

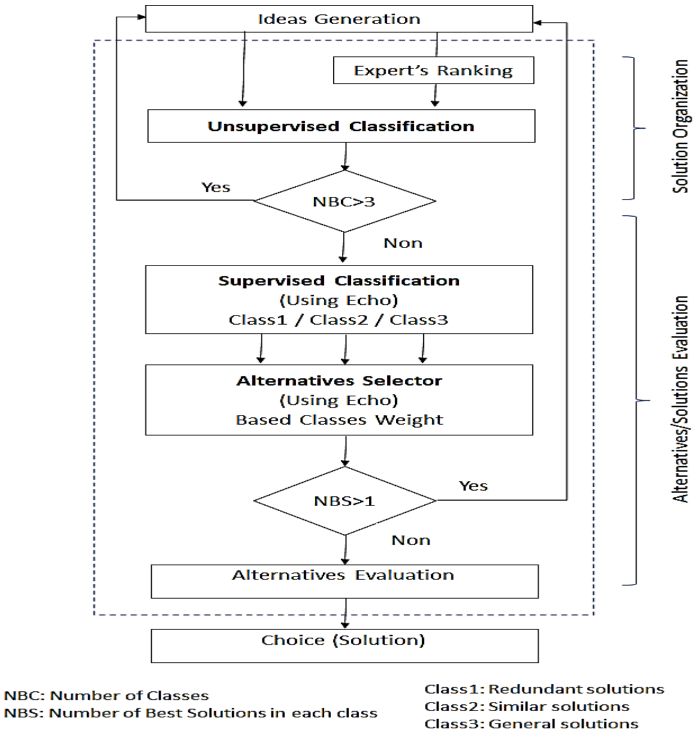


**Fig. 1.** Global flowchart: EHO applied in decision phase.

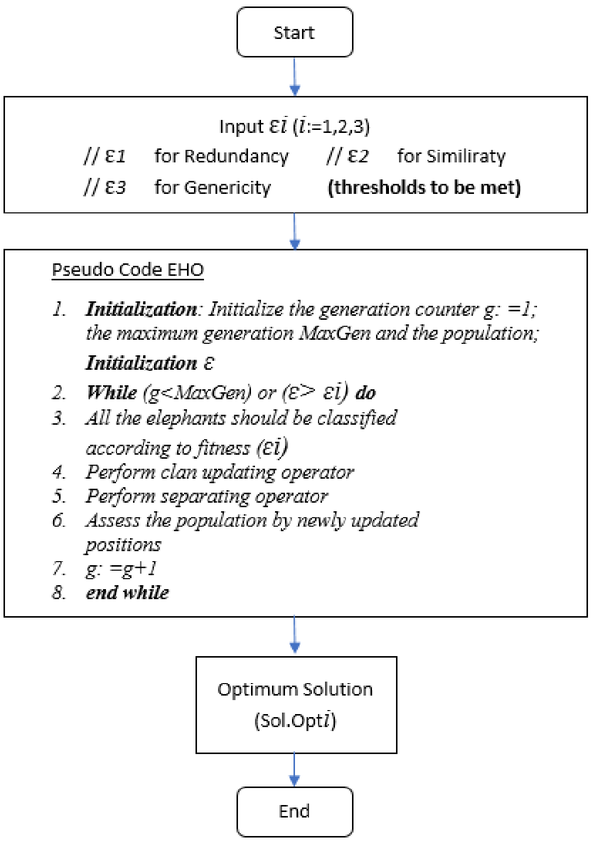


**Fig. 2.** Flowchart: Proposed model (supervised classification).

To perform alternative's selection phase, we use a number of classes obtained in the last phase. We calculate the weight of each class in relation to all classes, according to the following expression (norm): N$i$= |N$ci$|/∑ |N$ci$|   $i$=1...N,
where N is the number of classes and N$ci$ stands for the number of solution (population) in each class $ci$.

Then, a threshold should be set to maintain only the classes that have weights beyond the fixed threshold. The mentioned threshold can be defined using a learning algorithm or a simple value the human facilitator adjusts.

Applying this process, we get a reduced number of classes (important sets of solutions), where every matriarch represents the best solution in its class. A set of best solutions are sent to decision-makers for evaluation (choice selection).

To illustrate the alternative's selection phase, we use the following example:

**Table 1.** Alternative's selection example.

| Class | Number of solutions | N$ci$ |
|---|---|---|
| 1 | 5 | 0.125 |
| 2 | 20 | 0.500 |
| 3 | 15 | 0.375 |

If threshold= 0.2 then the maintained classes are 2 and 3.

If threshold= 0.4 then the maintained class is 3.

If threshold= 0.1 all the classes are maintained.

In our study, the facilitator and the human decision-makers exchange only texts. The idea here is to consider solutions or texts exchanged by decision-makers as documents representing them by vectors of features and compare these documents by measuring the distance between them. We propose to use several fitness functions depending on the case, redundancy, similarity or genericity.

## 4. Case study

We consider the breakdown diagnosis application in a complex industrial system. This kind of system makes decisions known and listed in appropriate documentation.

The expert decision-makers propose all possible solutions to the problem. Given the set of alternatives generated by the decision-makers, the screening and sorting tool will process these alternatives in two steps: the first involves the application ontology. The outputs of this step are synonymous, conflict and generalized alternatives. When two alternatives are conflicting, the facilitator has to remove one. "Restore-the-connection-of-the-resolver-plug" conflicts with "change-he-cable-resolver", the facilitator has chosen to remove "change-the-cable-resolver". Thus, the latter don't appear in the following step.

During an online meeting about the causes of computer failure (Known by Blue Screen), 11 Decision-makers try to find the right cause of this issue. The meeting passes through the following steps:

1) Ideas generation (Brainstorming),
2) Solutions Organization,
3) Solutions Evaluation.

During Step 1, the decision-makers share their ideas. Each decision-maker can share different ideas expressed in words. Other decision-makers can be influenced by the ideas expressed, which can generate more ideas. After brainstorming, step 2 comes where an unsupervised classification process is applied to classify ideas. If the number of classes is large (>3) then a refinement is necessary and the experts are asked to concentrate and refine their solutions (Repeating the brainstorming session).

In our case, the decision-makers give a set of solutions during their meeting. We use the term “word” to indicate solutions provided by decision-makers. The details are represented in Appendix A.

**5. Conclusion**

This paper presents a bio-inspired approach to support the facilitator and a tool to support the facilitator in the organizing stage of the process. We have developed a model using the EHO algorithm to optimize alternative screening tasks.

In this paper, we considered the support given to facilitators, particularly in distributed group decision-making. The main contribution and what is innovative in our work are twofold: 1) Incorporating a model of the decision-making process and 2) using a bio-inspired optimization method, in this case, EHO algorithm. The selected model embedded into the GDSS provides a detailed view of the decision-making process and enables intelligent decisional guidance. The particular facilitation techniques the facilitator focuses on at various times depending on the particular stage of the meeting process. As for the EHO algorithm, using this technique can find much better solutions to most benchmark problems than most bio-inspired optimization techniques.

Regarding the high complexity of the domain application, this paper only focuses on supporting group decision-making facilitation. Certain directions must be taken to develop more functional capabilities for the future, such as offering facilitators and decision-makers some feedback about the evolution of the decision-making sessions from a broad point of view, the levels of participation of decision-makers and the evolution of ideas.

The system may display a set of charts showing data on the number of discussion elements read by each participant, the number of elements contributed, the frequency of connections, the number of tasks for which each person has been a candidate, the number of tasks achieved, etc. This tool will be particularly useful for the coordination function. The main goals are to reduce the time required to come to a decision, particularly in a contingency situation, to compensate for the lack of experience of young operators, and to distribute available experience to different sites.

## **Appendix A.** Detailed calculations

| NO. | Response |
|---|---|
| 1 | Graphic card driver |
| 2 | Sound driver |
| 3 | Processor overheating |
| 4 | Software not compatible |
| 5 | Virus infection |
| 6 | Graphic Driver |
| 7 | Motherboard issue |
| 8 | Display driver |
| 9 | Overheating causing display and sound problem |
| 10 | Pilot of sound |
| 11 | Driver Audio |
| 12 | Processor heating |
| 13 | Processor Ventilation Problem |
| 14 | Software not suitable |
| 15 | Software Problem |
| 16 | Viral infection |
| 17 | Virus Problem |
| 18 | Virus that blocks software and drivers |

**Step 1.** In initial brainstorming round, the decision-makers give the following solutions (ideas):

| | A | B | C | D | E | F | G | H |
|---|---|---|---|---|---|---|---|---|
| **DM1** | 11 | 17 | 18 | | | | | |
| **DM2** | 4 | 5 | 6 | 7 | 11 | 13 | | |
| **DM3** | 1 | 9 | 12 | 14 | | | | |
| **DM4** | 1 | 4 | 9 | 12 | 13 | | | |
| **DM5** | 11 | 17 | 18 | | | | | |
| **DM6** | 3 | 4 | 5 | 6 | 7 | 10 | 15 | 18 |
| **DM7** | 5 | 7 | 8 | 11 | 13 | 14 | | |
| **DM8** | 6 | 16 | 18 | | | | | |
| **DM9** | 8 | 9 | 18 | | | | | |
| **DM10** | 2 | 8 | 9 | 16 | | | | |
| **DM11** | 1 | 4 | 9 | 13 | | | | |

In each round among 4, K-means algorithm is applied. The process is repeated until obtaining 3 classes.

The results of the last brainstorming are:

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 | Obs | Class | Distance to centroid |
|---|---|---|---|---|---|---|---|---|---|---|
| **DM1 =A** | 9 | 11 | 17 | 18 | | | | Obs1 | 1 | 6.864 |
| **DM2 =B** | 4 | 5 | 6 | 7 | 9 | 11 | 13 | Obs2 | 2 | 2.404 |

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 | Obs | Class | Distance to centroid |
|---|---|---|---|---|---|---|---|---|---|---|
| **DM3 =C** | 1 | 9 | 12 | 14 | | | | Obs3 | 1 | 5.667 |
| **DM4 =D** | 1 | 9 | 12 | 13 | 14 | | | Obs4 | 3 | 7.071 |
| **DM5 =E** | 9 | 11 | 17 | 18 | | | | Obs5 | 1 | 6.864 |
| **DM6 =F** | 3 | 4 | 5 | 8 | 9 | 10 | 18 | Obs6 | 2 | 3.972 |
| **DM7= G** | 5 | 7 | 8 | 9 | 11 | 13 | 14 | Obs7 | 2 | 3.621 |
| **DM8 =H** | 6 | 16 | 18 | | | | | Obs8 | 3 | 14.933 |
| **DM9 =I** | 9 | 11 | 18 | | | | | Obs9 | 1 | 13.510 |
| **DM10 =J** | 2 | 8 | 9 | 11 | 16 | | | Obs10 | 3 | 8.426 |
| **DM11 =K** | 1 | 6 | 9 | 13 | | | | Obs11 | 1 | 8.217 |

The number of classes <=3, then the solutions organization step (Unsupervised classification) ends and begin the next step.

**Step 2.** A supervised classification algorithm (adapted EHO) version is applied. We consider the following terms:

- **Population**, which is the set of solutions given by the decision-makers.
- **Clan**, the population is divided into a finite number of clans (subsets of the solutions).

Our objective is to classify the redundant solutions and general ones, so our fitness function must be the distance between solutions. The following process is repeated until a ***Max generation*** is reached or **Stop condition** is satisfied.

1) Calculation of distance between clan members according to the following fitness function:

$$fitness_{x,ci} = \sum_{j=1}^{nci} dist_{x,j}$$

$c_i$ is the clan;

j is a member of the clan;

and $dist_{x,j}$ is the distance between elements *x* and *j* used in strings data case.

$$dist_{x,j} = \frac{\boldsymbol{ComWords}_{x,j}{}^{2}}{|x| * |j|}$$

and ***ComWords*** is the number of common words between *x* and *j* members.

The treatment of **similarities** differs from that of **redundant** and **generals** because it is based on the notion of semantics. Therefore, two treatments are envisaged:

- Treatment of redundant and generals where the common words number between two members is calculated using:

$$ComWords_{x,j} = \sum_{i=1}^{n} P(wi) \ / \begin{Bmatrix} P(wi) = 1 & if\ wi\epsilon(x \cap j) \\ P(wi) = 0 & else \end{Bmatrix} \quad where\ n = \min(|x|, |j|)$$

- Treatment of similar requires synonyms. For this purpose, a correspondence table is needed.

The common words number is calculated using:

$$ComWords_{x,j} = \sum_{i=1}^{n} P(wi) \ / \begin{Bmatrix} P(wi) = 1 & if\ wi\epsilon(x \cap (syn(j) \cup j)) \\ P(wi) = 0 & else \end{Bmatrix}$$

where n=*min* (| x |, | j |) and syn(j) is the set of synonyms of the member j

2) After experimentations, thresholds are fixed:
   - If fitness value is equal to 1 then the terms are redundant or similar if using synonyms.
   - If fitness value is between 0.75 and 0.99 then it is a generality case.
3) The member having the minimum fitness (worst position) in the clan is separated away from clan.
4) The separated members are replaced, **Goto 1**.

**Redundant and general treatment**

***Initial parameters***

Population size=11 /*11 solutions */

Clan number =2

Clan size=4

***Generation1***

| **Clan 1** | **B** | **C** | **F** | **H** | **Fitness** | **Clan 2** | **D** | **G** | **J** | **K** | **Fitness** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **B** | | 0.036 | 0.184 | 0.048 | 0.267 | **D** | | 0.2571 | 0.04 | 0.45 | 0.747 |
| **C** | | | 0.036 | 0.000 | **0.071** | **G** | | | 0.2571 | 0.3214 | 0.836 |
| **F** | | | | 0.048 | 0.267 | **J** | | | | 0.05 | **0.347** |
| **H** | | | | | 0.095 | **K** | | | | | 0.821 |

Redundant= {}, General= {}.

<u>Separation:</u>

Separate C from clan 1 and replace it by E.

Separate j from clan 2 and replace it by C.

***Generation 2***

| **Clan 1** | **B** | **E** | **F** | **H** | **Fitness** | **Clan 2** | **C** | **D** | **G** | **K** | **Fitness** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **B** | | 0.142 | 0.142 | 0.083 | 0.369 | **C** | | **0.800** | 0.143 | 0.250 | 1,193 |
| **E** | | | 0.142 | 0.083 | 0.369 | **D** | | | 0.257 | 0.450 | 1,507 |
| **F** | | | | 0.047 | 0.333 | **G** | | | | 0.321 | **0.721** |
| **H** | | | | | **0.214** | **K** | | | | | 1,021 |

Redundant= {}, General= {(D, C)}. *D is more general than C.*

<u>Separation:</u>

Separate H from clan 1 and replace it by A.

Separate G from clan 2 and replace it by H.

***ansGeneration 3***

| **Clan 1** | **A** | **B** | **E** | **F** | **Fitness** | **Clan 2** | **C** | **D** | **H** | **K** | **Fitness** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **A** | | 0.143 | **1.000** | 0.143 | 1.286 | **C** | | **0.800** | 0.000 | 0.250 | 1.050 |
| **B** | | | 0.143 | 0.184 | **0.469** | **D** | | | 0.000 | 0.450 | 1.250 |
| **E** | | | | 0.143 | 1.286 | **H** | | | | 0.321 | **0.321** |
| **F** | | | | | 0.469 | **K** | | | | | 1.021 |

Redundant= {(A, E)}, General= {(D, C)}.

Separation:

separate H and replace it by A

separate G and replace it by H

***Generation 4***

| **Clan 1** | **A** | **E** | **I** | **F** | **Fitness** | **Clan 2** | **B** | **C** | **D** | **K** | **Fitness** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **A** | | **1.000** | **0.750** | 0.143 | 1.893 | **B** | | 0.036 | 0.114 | 0.321 | **0.471** |
| **E** | | | **0.750** | 0.143 | 1.893 | **C** | | | **0.800** | 0.250 | 1.086 |
| **I** | | | | 0.190 | 1.690 | **D** | | | | 0.450 | 1.364 |
| **F** | | | | | **0.476** | **K** | | | | | 1.021 |

Redundant={(A,E)}, General={(D,C),(A,I),(E,I)}.

***Stopping condition***

The generation stops because the separated members cannot be replaced, all free members have already left the clans.

**Similar calculation**

At this stage, the set of solutions should be reduced because identical and general solutions are already treated.

The following table contains the remained solutions.

| | **C1** | **C2** | **C3** | **C4** | **C5** | **C6** | **C7** |
|---|---|---|---|---|---|---|---|
| B | 4 | 5 | 6 | 7 | 9 | 11 | 13 |
| F | 3 | 4 | 5 | 8 | 9 | 10 | 18 |
| G | 5 | 7 | 8 | 9 | 11 | 13 | 14 |
| H | 6 | 16 | 18 | | | | |
| J | 2 | 8 | 9 | 11 | 16 | | |
| K | 1 | 6 | 9 | 13 | | | |

We propose the following correspondence table of synonyms

| **Synonyms** |
|---|
| (1,6,8) |
| (2, 10. 11) |
| (4, 14, 15) |
| (3, 12, 13) |

(5, 16, 17, 18)
(7)
(9)

***Initial parameters***

Population size=6 /*6 solutions */

Clan number =1 /*binary classification similar or not*/

Clan size=3

***Generation 1***

| Clan1 | B | F | K | Fitness | |
|---|---|---|---|---|---|
| **B** | | 0.735 | 0.321 | 1.056 | Similar = {} |
| **F** | | | 0.321 | 1.056 | Separation: separate K and replace it by G. |
| **K** | | | | **0.643** | |

***Generation 2***

| Clan 1 | B | F | G | Fitness | |
|---|---|---|---|---|---|
| B | | 0.735 | **1.000** | 1.735 | Similar = {(B, G)} |
| **F** | | | 0.735 | **1.469** | Separation: |
| **G** | | | | 1.735 | separate F and replace it by H. |

***Generation 3***

| Clan 1 | B | G | H | Fitness | |
|---|---|---|---|---|---|
| **B** | | **1,000** | 0.048 | 1,048 | Similar = {(B, G)} |
| **G** | | | 0.190 | 1,190 | Separation: |
| **H** | | | | **0.238** | separate H and replace it by J. |

***Generation 4***

| Clan 1 | B | G | J | Fitness | |
|---|---|---|---|---|---|
| **B** | | **1.000** | 0.457 | 1.457 | Similars = {(B, G)} Separation: |
| **G** | | | 0.457 | 1.457 | |
| **J** | | | | **0.914** | separate J |

***Stopping condition***

The generation stops because the separated members cannot be replaced; all free members have already left the clans.

The final result is:

Class of redundant={(A,E)}

Class of general= {(D, C), (A, I), (E, I)}.

Class of similar = {(B,G)}

## References

Adam, F. (2012). 20 years of decision-making and decision support research published by the Journal of Decision Systems. Journal of Decision Systems, 21(2) 93- 99.

Adla, A. (2010). Facilitation Support for Group Decision-making : a Tool and a Model Proposal. PhD Thesis, Paul Sabatier University Toulouse III, Toulouse France.

Adla, A., Zarate, P., & Soubie, J. L. (2011). A proposal of toolkit for GDSS facilitators. Group Decision and Negotiation, 20. 57-77.

Carneiro, J. (2021). Group decision support systems for current times: Overcoming the challenges of dispersed group decision-making. Neurocomputing, 423, 735-746.

Darwish, A, (2018). Bio-inspired computing: Algorithms review, deep analysis, and the scope of applications, Future Computing and Informatics Journal, 3(2), 231-246.

Fan, X., Sayers, W. & Zhang, S. (2020). Review and classification of bio-inspired algorithms and their applications. Journal of Bionic Engineering, 17, 611-631.

Ismael, AK. (2019). Enhanced elephant herding optimization for global optimization. IEEE Access, 7, 34738-34752.

Gad, A. G. (2022). Particle swarm optimization algorithm and its applications: a systematic review. Archives of Computational Methods in Engineering, 29(5), 2531-2561.

Mahraz, A. O., Bouhalouan, D., & Adla, A. (2016). Facilitating virtual group decision-making . Procedia Computer Science, 83, 1050-1055.

Mumali, F. (2022). Artificial neural network-based decision support systems in manufacturing processes: A systematic literature review, Computers & Industrial Engineering, 165, 107964.

Paneerselvam, S. (2020). Role of AI and Bio-Inspired Computing in Decision-making . Internet of Things for Industry 4.0: Design, Challenges and Solutions, 115-136.

Rahman, N & De Feis, G. (2009). Strategic Decision-Making: Models and Methods in the Face of Complexity and Time Pressure. Journal of General Management., 35, 43-59.

Shim, JP., Warkenti, M. & Coutney, JF. (2002). Past, present, and future of decision support technology. Decision support systems, 33(2), 111-126.

Wu, H. & Xu, Z. (2020). Fuzzy Logic in Decision Support: Methods, Applications and Future Trends. International Journal of Computer Communications and Control, 16(1), 4044.

Wang, G. G., Deb, S., Gao, X. Z., & Coelho, L. D. S. (2016). A new metaheuristic optimisation algorithm motivated by elephant herding behaviour. International Journal of Bio-Inspired Computation, 8(6), 394-409.

Yang, X.S. (2021). Genetic Algorithms. In Nature-Inspired Optimization Algorithms (Second edition), 91-100.

Zheng, Y., Lu, X., Zhang, M., Chen, S., Zheng, Y., Lu, X., ... & Chen, S. (2019). Biogeography-based optimization (pp. 27-49). Springer Singapore.