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Research Article

Bio-Inspired Optimization Method Supported Distributed Group Decision Making

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ABSTRACT

Distributed Group Decision Meeting (DGDM) is a multi-party decision problem where two or more independent concerned parties must make a joint decision. Group decision meetings consume a great deal of time and effort in organizations. To support these processes, Distributed Group Decision Support Systems (DGDSS) are used. They intended to provide computational support to collaborative decision-making 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, many DGDSS embed some facilitation mechanisms and are currently being used with the help of a human facilitator who guides the group members through the decision-making process. We consider in this article a framework for distributed group facilitation that supports facilitators by incorporating a model of the decision-making process which provides a detailed view of the decision-making process. Based on a model of the decision-making process, group facilitation tasks are automated, at least partially, to increase the ability of a facilitator to monitor and control the group decision meeting process. Decision support approaches such bio-inspired optimization methods potentially offer these capabilities and can assist the facilitator and decision-makers in presenting the alternatives in a form that facilitates the decision making. The developed system is based on Elephant herding optimization (EHO) whilst the evaluation is mainly based on Analytic Hierarchy Process (AHP).

Keywords: Group decision making, Group Decision Support Systems, Bio-Inspired Optimization Methods, EHO Algorithm.

INTRODUCTION

The performance of groups interacting with Distributed Group Decision Support Systems (DGDSS) has been the heart of the issues raised in numerous studies [1][2]. DGDSS does not address areas of group functioning, such as decision meeting design or managing verbal communications [3]. These and other facilitation activities must come from people because of the great interest of the facilitator.

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An integration of good computer tools with effective human facilitation can lead to a more effective meeting than either by itself. 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 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 knowing when to employ particular techniques to move the group towards congruence [4].

We consider in this article 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 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 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.

ARTIFICIAL INTELLIGENCE METHODS TO SUPPORT DISTRIBUTED 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 [5]. The latter use 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 out of the uncertainty or ambiguity, learning through experience, react in a timely manner to a new or an adaptive situation: Handling perplexing solutions, use knowledge to recognize various factors in a decision), they make intelligent support for group decision making [6]. Intelligent decision making has been growing and emerging as powerful tools by using various AI techniques such as Artificial neural networks (ANN) [7], Fuzzy logic (FL) [8], and Bio-inspired algorithms [9][10]. Bio inspired algorithms are revolutionary techniques for solving hard and complex problems. They aimed to find the optimal solution, to solve problems maintaining perfect balance among their 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 a longer time to converge. Bio-inspired algorithms possess the following capabilities: Applicable to wide range of problems, few control parameters to tune the algorithm, and better convergence rate while reaching the optimum value [11].

Elephant herding optimization (EHO) [12][13] 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 optimization, combinatorial optimization, constrained optimization, and multi-objective optimization are reviewed. The superiority of the EHO method to several state-of-the-art metaheuristic algorithms has been demonstrated for many benchmark problems and in various application areas. EHO algorithms can find much better solutions on most benchmark problems than three other algorithms (Biogeography-Based Optimization (BBO) [14] and Genetic Algorithms (GA) [15]. Based on the experimental results, researchers concluded that EHO has good characteristics as optimization algorithm, and it performs better than PSO algorithm [12] that was used for comparison.

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

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

The purpose of our work is 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).

A. Elephant herding optimization (EHO) algorithm

Elephant herding optimization (EHO) algorithm is a recently bio-inspired meta-heuristic algorithm proposed in [16]. This search algorithm is invented by simulating elephant herds' biological behaviors. In nature, elephant is considered as a social animal and the herding consists of several clans of female, elephant and their calves. Each clan moves under the influence of a matriarch or a leader elephant. The female elephant uses to live with their family groups while the male elephant separated when they grow up and live in contact with their family group using low frequency vibrations. Based on these biological behaviors, an algorithm of male elephant focuses on global exploration and 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 in the same time each clan has fixed number of elephants.
2) At each generation, a fixed number of males will leave their family group and live far away.
3) In each clan, the elephants live together under the leader called a matriarch.

The herding behavior is mathematically decomposed into two types of operators: one is updating operator and another is separating operator. The algorithm is mathematically modelled and is given by Algorithme01.

Algorithm 01 Pseudo code of EHO

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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*

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

$$x_{new,ci,j} = \beta * x_{center,ci} \qquad (2)$$

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

And 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*

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

B. 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):

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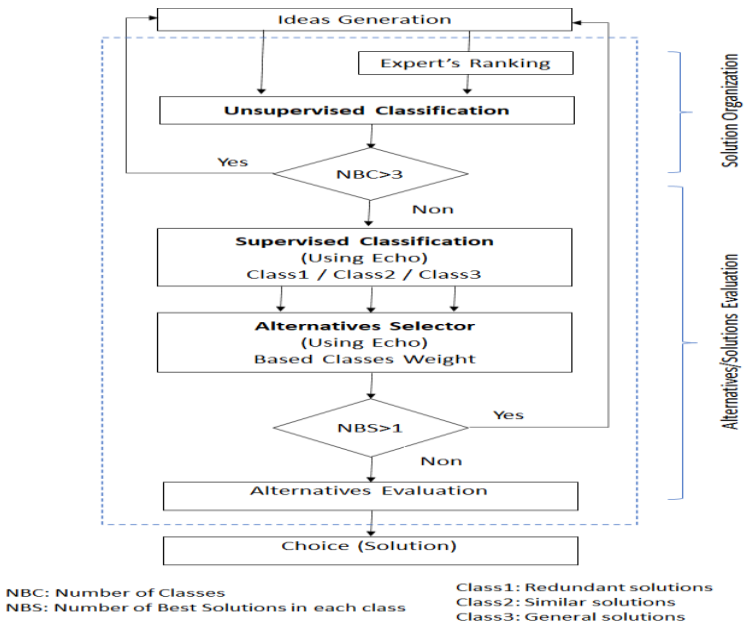

Fig. 1: Global flowchart: EHO applied in decision phase

1) Each alternative expressed by the decision-maker is represented by one elephant

2) Each clan obtained after classification represents a class of ideas considered homogeneous.

C. Model development

This model concerns the second phase (learning during supervised classification) which aims to find the proper values of ε1, ε2 and ε3 that validate the model. For each parameter (εi) we get a class (Sol. Opti) which will be used in the next phase (Alternative's selector phase), as shown in figure (Figure 2):

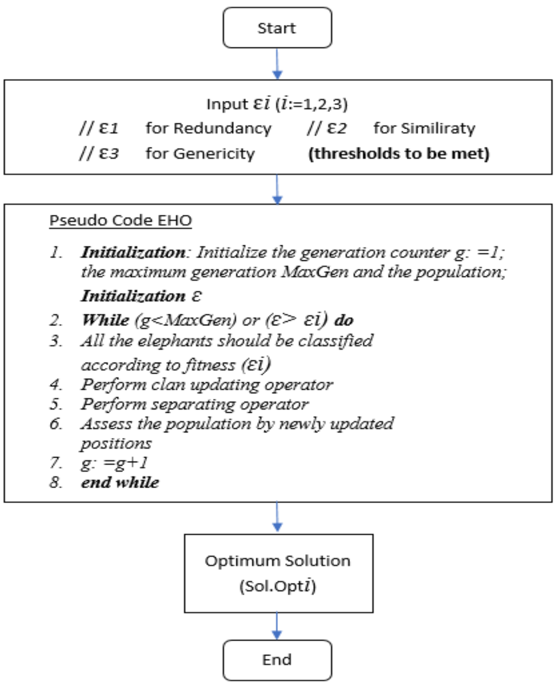

Fig. 2: Flowchart: Proposed model (supervised classification)

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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):

$Ni= |Nci|/\sum |Nci|$ i=1..N

where N is the number of classes

N*ci* : number of solutions (population) in each class *ci*.

Then a threshold should be set to maintain only the classes having weight beyond the fixed threshold. The mentioned threshold can be defined using a learning algorithm or a simple value adjusted by the human facilitator.

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:

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 by texts. The idea here is to consider answers or texts exchanged by decision-makers as documents representing them by vectors of features and to compare these documents by measuring distance between their features. We propose using several fitness functions depending on the case, redundancy, similarity or genericity.

CASE STUDY

We consider the breakdowns diagnosis application in a complex industrial system. In this kind of system, decisions are 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 group of decision makers, the screening and sorting tool will process these alternatives in two steps: the first one involves the application ontology. The outputs of this step are synonymous, conflict and generalized alternatives (see Fig. 7). When two alternatives are conflicting, the facilitator has to remove one.

"restore_the_connection_of_the_resolver_plug" is conflicting with "change_the_cable_resolver", the facilitator has chosen to remove "change_the_cable_resolver". Thus, the latter don't appear in the following step.

During online meeting about the causes of computer failure (Known by Blue Screen), the 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 Step1, 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 refinement is necessary, and the experts are asked to concentrate and refine their answers (Repeating the brainstorming session).

In our case, the decision-makers give a set of answers during their meeting. We use the term "word" to indicate answers provided by decision-makers.

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

RESULTS

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

	A	**B**	**C**	**D**	**E**	**F**	**G**	**H**
DM1	11	17	18					
DM2	4	5	6	7	11	13		

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

Obs	Class	Distance to centroid
Obs1	1	6,864
Obs2	2	2,404
Obs3	1	5,667
Obs4	3	7,071
Obs5	1	6,864
Obs6	2	3,972
Obs7	2	3,621

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Obs8	3	14,933
Obs9	1	13,510
Obs10	3	8,426
Obs11	1	8,217

The number of classes <=3, then the solutions organization step (Unsupervised classification) ends and begins 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 answers given by the decision-makers.
- **Clan**, the population is divided into a finite number of clans (subsets of the answers).

Our objective is to classify the redundant answers and general ones, so our fitness function must be the distance between answers. 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$_i$;

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:

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

$$where\ n = \min(|x|, |j|)$$

- Treatment of similars 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 answers */

Clan number =2

Clan size=4

Generation1

Clan 1	**B**	**C**	**F**	**H**	**Fitness**
B		0,036	0,184	0,048	0,267
C			0,036	0,000	**0,071**
F				0,048	0,267
H					0,095

Clan 2	**D**	**G**	**J**	**K**	**Fitness**
D		0,2571	0,04	0,45	0,747
G			0,2571	0,3214	0,836
J				0,05	**0,347**
K					0,821

Redundant= {}, General= {}.

Separation:

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**
B		0,142	0,142	0,083	0,369
E			0,142	0,083	0,369

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F				0,047	0,333
H					**0,214**

Clan 2	**C**	**D**	**G**	**K**	**Fitness**
C		**0,800**	0,143	0,250	1,193
D			0,257	0,450	1,507
G				0,321	**0,721**
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.

Generation 3

Clan 1	**A**	**B**	**E**	**F**	**Fitness**
A		0,143	**1,000**	0,143	1,286
B			0,143	0,184	**0,469**
E				0,143	1,286
F					0,469

Clan 2	**C**	**D**	**H**	**K**	**Fitness**
C		**0,800**	0,000	0,250	1,050
D			0,000	0,450	1,250
H				0,321	**0,321**
K					1,021

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

<u>Separation:</u>

separate H and replace it by A

separate G and replace it by H

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Generation 4

Clan 1	**A**	**E**	**I**	**F**	**Fitness**
A		**1,000**	**0,750**	0,143	1,893
E			**0,750**	0,143	1,893
I				0,190	1,690
F					**0,476**

Clan 2	**B**	**C**	**D**	**K**	**Fitness**
B		0,036	0,114	0,321	**0,471**
C			**0,800**	0,250	1,086
D				0,450	1,364
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 treatment

At this stage, the set of answers should be reduced because identical and general answers are already treated. The following table contains the remained answers.

	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)

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(3, 12, 13)
(5, 16, 17, 18)
(7)
(9)

Initial parameters

Population size=6 /*6 answers */

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
F			0,321	1,056
K				**0,643**

Similars={}

<u>Separation:</u>

separate K and

replace it by G.

Generation 2

Clan 1	**B**	**F**	**G**	**Fitness**
B		0,735	**1,000**	1,735
F			0,735	**1,469**
G				1,735

Similars={(B,G)}

<u>Separation:</u>

separate F and

replace it by H.

Generation 3

Clan 1	**B**	**G**	**H**	**Fitness**
B		**1,000**	0,048	1,048
G			0,190	1,190
H				**0,238**

Similars={(B,G)}

<u>Separation:</u>

separate H and

replace it by J.

Generation 4

Clan 1	**B**	**G**	**J**	**Fitness**
B		**1,000**	0,457	1,457
G			0,457	1,457
J				**0,914**

Similars={(B,G)}

<u>Separation:</u>

separate J

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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)}

DISCUSSION

The experimental results demonstrate that the integration of the Elephant Herding Optimization (EHO) algorithm into the group decision-making process provides a systematic means of screening, classifying, and reducing alternatives generated during distributed meetings. The approach successfully identified redundant, general, and similar alternatives, thereby reducing the cognitive load on decision-makers and facilitating the subsequent evaluation and selection phases. This aligns with prior findings that bio-inspired optimization techniques are capable of handling large and complex search spaces efficiently, often outperforming conventional heuristics in convergence speed and solution quality [9]. In our case study, the method achieved an 83% reduction in alternatives (from 18 initial responses to 3 refined classes), potentially saving up to 50% of meeting time in industrial settings by minimizing redundant discussions and accelerating consensus-building.

From a facilitation perspective, the EHO-based model provides clear advantages. The automation of redundancy and synonym detection supports the facilitator by minimizing repetitive discussions, which are often reported as a barrier to effective group decision support systems [4]. Moreover, the capacity of the algorithm to detect generalities among alternatives fosters structured knowledge organization, allowing facilitators to guide participants toward more focused deliberations. These findings are consistent with research emphasizing the value of computational aid in enhancing facilitator effectiveness and improving group efficiency [1]. Recent advances in bio-inspired algorithms further support this, as they have been applied to enhance decision-making in collective systems, drawing from natural behaviors to improve robustness in networked environments [17].

The case study application further highlighted the robustness of the method in real-world contexts. In the industrial breakdown diagnosis scenario, the EHO algorithm successfully reduced the set of alternatives into semantically distinct and relevant categories. This reduction is critical in distributed decision-making environments where the number of alternatives can grow rapidly and overwhelm participants. By filtering and structuring alternatives before evaluation, the proposed approach enhances decision quality while shortening the time required to reach consensus.

However, some limitations should be noted. First, the current implementation relies heavily on text-based exchanges and predefined synonym tables, which may constrain applicability in multilingual or highly technical domains where semantic relationships are more nuanced. Second, while the method proved efficient for a moderate number of alternatives, scalability to very large datasets remain to be fully tested. Additionally, the supervised classification phase still requires threshold adjustments by a human facilitator, indicating that the system does not yet achieve complete autonomy.

Overall, the results suggest that the proposed EHO-supported facilitation model can make distributed group decision-making processes more efficient and structured. By reducing redundancy, identifying

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semantic relations, and guiding the facilitator with optimized classifications, the approach contributes to bridging the gap between automated decision-support tools and human-centered facilitation. Future work should aim to extend semantic analysis capabilities, explore integration with natural language processing techniques, and assess scalability in larger and more diverse decision-making contexts.

CONCLUSION & FUTURE WORK

In this paper a bio-inspired approach is presented to support facilitator, and tool supports the facilitator in the organizing stage of the process. We have developed a model using EHO algorithm to optimize alternatives screening task.

We considered in this paper the support to facilitators particularly in distributed group decision making. The main contribution and what is innovative in our work is 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 decision-making process and enable intelligent decisional guidance. In facilitation techniques the facilitator focuses on at various times depend on the particular stage of the meeting process. As for the EHO algorithm, using this technique can find much better solutions on 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 to facilitator 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 lack of experience of young operators, and to distribute available experience to different sites.

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