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A Hybrid Honey-Badger Intelligence Algorithm with Nelder-Mead Method and Its Application for Reliability Optimization

Roaa aziz fadhil *, Zahir Abdul Haddi Hassan

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Abstract: The sophisticated foraging behavior of the honey badger approach inspired the metaheuristic algorithm known as the honey badger algorithm. In this article, we combine the honey badger algorithm with the Nelder-Mead algorithm to create a honey badger Nelder -Mead algorithm (HBANM). The experimental results and statistical analysis for optimization issues show that HBANM is more successful than HBA when used for solving optimization problems and multi-objective reliability system.

***Key words**: Nelder-Mead algorithm, honey-badger algorithm, reliability*

1. Introduction

Meta-heuristic optimization is the name of a sophisticated computational design that creates optimization strategies.By combining several operators and search techniques, the best answer is discovered. [8,10]. Many systems have been developed to enable meta-heuristics to converge local search techniques quickly. Most of these approaches combine meta-heuristics and local search techniques like the Nelder-Mead method to create more efficient processes with comparatively faster convergence [4,9]. We mention some of the works. For complex global optimization problems, genetic algorithms are often used in practice. However, they are less efficient for problems with local optimization. Although the Nelder-Mead simplex algorithm shares several traits with genetic algorithms, it results in the closest local minimum. According to the results of Griewank's test function employing a hybrid Nelder-Mead Simplex and Genetic algorithm, it was pretty efficient., especially for big dimensions. Results from the Corona test function supported this conclusion [7]. Because it doesn't require owning any infrastructure, cloud computing, one of the newest distributed system paradigms, allows for operations to be completed at lower costs. Scientific workflows are a series of calculations that facilitate the structured and unstructured examination of data. In the specified optimization issue, which is a multi-objective optimization work, make span, cost, energy, and flow time are addressed as the objective functions. By being evaluated in light of five different workflow case studies, the efficacy of a hybrid optimization technique based on the Grey Wolf Optimizer and Nelder Mead Method (GWO-NM), has been shown. [14]. The application of a hybrid algorithm composed of modification Nelder Mead the is directional derivatives simplex (DDS) and interpolated Ant Colony Optimization Algorithm (IACO-DDS) to identify the time delays in the linear plant. The research was carried out on sixteen plants using random characteristics and divided into two groups based on how easy or difficult they were to identify. The hybrid method IACO-DDS speeds up search times by using the directional derivatives simplex (DDS) local search algorithm to improve the algorithms Ant Colony(IACO) results in a single iteration. Only in demanding multimodal search environments where local information is used may an early convergence and the achievement of a local optimum occur.. [16] hybridization of the Cuckoo Search (CS) consists of combining the Cuckoo Search (CS) with the Nelder-Mead method. Employed to maximize the efficiency of multicellular solar systems, the technique performs better in this application. [11]. This paper proposes

Department of Mathematics
College of Education for Pure Sciences University of Babylon
Email: roaaazizfadhil@gmail.com,roaa.fadhil.pure256 @student.uobabylon.edu.iq*
E-mail: mathzahir@gmail.com

development honey badger algorithm (HBA) [3] with Nelder - Mead algorithm [4,9], hybrid honey badger Nelder - Mead algorithm (HBANM). This The effectiveness of HBANM verified by the experimental results statistical analysis for optimization problems reveal HBANM is superior to HBA and applied HBANM for multi-objective reliability systems [13] and takes into account several objectives, such as maximizing reliability and minimizing costs [1,2 12,13,17] results show HBANM improved reliability system value that compared to HBA.

2. Preliminaries

2.1 The Honey Badger Algorithm

The Honey Badger Algorithm (HBA) [3] mimics the badger's method of searching for food. The two ways the badger can find food supplies are via digging and smelling or by following a honeyguide bird. The terms "digging mode" and "honey mode" are used to describe the first and second situations, respectively. The badger uses its sense of smell to roughly find its prey in the first instance. When it does, it swerves to avoid it and choose a better spot to dig and capture its victim. In the second scenario, the badger locates the hive by using the honeyguide bird's guide.

Every badger in the population is represented by its position $x_i = [x_{i1}, x_{i2}, \ldots, x_{iD}]$, where D signifies the number of variables and $I = 1, 2, 3, \ldots, N$, where N represents population size. using the following equation[1]

$$x_i = \ell b_i + r_1 \times (\mathcal{u} b_i - \ell b_i) \quad \ldots (1)$$

where x_i indicates the location of the (ith) honey badge,and ℓb_i and $\mathcal{u} b_i$ stand for the lower limit and upper bound, respectively, in the search domain. In addition, r_1 is a randomly generated value between 0 and 1.the dependent intensity will be calculated in the following step. Intensity is related to the prey's level of concentration and the distance between it and the honey badger. is the strength of the scent emanating from the prey; if the scent is potent, the motions will be quick, and vice versa.

$$I_i = r_2 \times \frac{S}{4\pi d_i^2}$$

Where $S = (x_i - x_{i+1})^2$, $d_i = x_{prey} - x_i$

Using the honey badger's current position, x_i, and its subsequent position, x_{i+1}, S is determine concentration intensity. di the distance between the honey badger's present location and its prey's position x_{prey} The density factor(α) ensures a seamless shift of HBA from global exploration to local development. and r_2 is a random value between [0, 1], also has the following mathematical model[3]

$$\alpha = C \times exp\left(\frac{-t}{t_{max}}\right) \quad \ldots (3)$$

Where t representing the current iteration, t_{max} the most iterations allowed, and C is a constant with a value more than one. The next two steps of HBA are digging and honey. In the global exploration stage, the movement of the honey badger population along the heart shaped line, which has the following mathematical expression [3]

$$x_{new} = x_{prey} + \mathrm{F} \times \beta \times I \times x_{prey} + \mathrm{F} \times \mathrm{r}_3 \times \alpha \times \mathrm{d}_i \times \left|\cos(2\pi r_4) \times [1 - \cos 2\pi r_5]\right| \ldots (4)$$

where three distinct random numbers r_3, r_4, and r_5 are used the range [0, 1] of numbers the prey's position that has been determined to be ideal thus far is represented by x_{prey} .

$\beta \geq 1$is a symbol of the honey badger's capacity to obtain food, during the digging process, depending on the value of a flag F, the search direction is modified to thoroughly search the search space. The following equation [3] calculates it:

$$F = \begin{cases} 1 & , if\ r_6 \leq 0.5 \\ -1 & , \text{otherwise.} \end{cases} \quad (5)$$

Where $r_6 \in [0,1]$

Finally, equation (6), The honey phase depicts a honey badger's behavior as it approaches the beehive by following a honeyguide bird, and it is represented by (6)[3]

$$x_{new} = x_{prey} + F \times r_7 \times \alpha \times d_i \quad \ldots (6)$$

that a badger conducts a search close to the $prey$ location x_{prey} already identified. Time varying search behavior (α) is influencing the search at this point. A honey badger may also detect disturbance F.

ALGORITHM 1: Pseudo code of the HBA

Step1: Set the parameters initialized t_{max} , β, C.
Step2: Set the initial number of options (N).
Step3:Use an objective function to assess each honey badger position's fitness, and assign to f_i, i ∈ $[1, 2, \ldots, N]$.
Step 4:Assign fitness to f_{prey} and save the optimal position for x_{prey} .
Step5: Repeat
Step 6: Utilizing equation (3), update the decreasing factor
Step7:Equation (2)should be used to calculate the intensityI_i.
Step8: for i : 1 to N do
Step 9: if $r < 0.5$ then
Step10:Equation (4) is used to update the location x_{new}.
Setp11: Else
Step12:By utilizing equation(6), modify position x_{new}
Step13: end if Assess the new position, then give it to f_{new} .
Step14:if $f_{new} \leq f_i$ then
Step15:Set $x_i = x_{new}$and $f_i = f_{new}$.
Step16:end if $f_{new} \leq f_{prey}$ then
Step17: Set $x_{prey} = x_{new}$and $f_{prey} = f_{new}$
Step18 end if
Step19 end for the iteration (t) criterion has been satisfied.
Step20:Return the x_{prey}

2.2 The Nelder-Mead algorithm

These are the steps that make up the NM simplex algorithm [4,9].

Step1: Initialization: In the search space, an initial simplex with $n + 1$ vertices are constructed $(x_1, x_2, \ldots, x_{n+1})$, and the appropriate function values for each vertex are determined $f(x_i)$

Step 2 : Order the n + 1 vertices to determine the best *point* x_b, And The vertex x_g with the second highest function value and the vertex x_w with the worst, function value, the centroid of every point With exception of x_w , which is determined as

$$x_c = \frac{1}{n} \quad \ldots (7)$$

Step 3:Reflection the calculated reflected point is

$$x_r = x_c + \lambda(x_c - x_w) \quad \ldots (8)$$

Here, $\lambda > 0$ and is typically set to 1. The highest value point relative to the centroid is reflected. Usually, this causes the simplex to travel from high regions to lower parts

If $f(x_r) < f(x_b)$the algorithm continues with expansion ; If $f(x_b) \leq f(x_r) < f(x_g)$, replace x_g by $x_r$and terminate the iteration.

Step 4: Expansion It is calculated that the expanded point is

$$x_e = x_c + \mu(x_r - x_c) \quad \ldots$$

Here, $\beta > max\ (1, \alpha)$ and is typically set to 2. similar to reflection, except the point that is reflected is sent further. And If $f(x_e) < f(x_b)$, replace the point x_w by x_e otherwise, the
In every other case, then accept x_r and end the iteration.

Step 5- Contraction The calculated contracted point is If $f(x_r) \geq f(x_g)$ A contraction takes place. Two contractions are conceivable.

Outside: *If* $f(x_r) < f(x_w)$ contraction by the formulae (10)

$$x_{con} = x_c + \sigma(x_r - x_c) \quad ,0 \leq \sigma \leq 1 \quad \ldots(10)$$

If $f(x_{con}) < f(x_r)$ *then* accept x_{con} and end the iteration. otherwise perform a shrink operation

Inside ,If $f(x_r) \geq f(x_w)$ apply the formulas (11) to the inside contraction

$$x_{con} = x_c + \sigma(x_w - x_c) \quad 0 \leq \sigma \leq 1 \quad ..(11)$$

If $f(x_{con}) < f(x_w)$ then accept x_{con} and end the iteration. otherwise perform a shrink operation

Step 6- Use the following equation (12) to shrink all points except point best to produce a simplex for the next iteration.

$v_i = x_1 + \delta(x_i - x_1), 0 < \delta < 1$

$i = 2, \ldots, n + 1$ …(12)

3. The Proposed HBANM Algorithm

The suggested honey badger Nelder -Mead algorithm (HBANM) follows the same steps the conventional The Honey Badger Algorithm (HBA) then Then apply solution obtained from HBA algorithm in the Nelder-Mead algorithm for Same of iteration, to improve the best result from the previous step of the HBA algorithm.

3.1 Experimental results

Evaluate performed to the performance of the proposed method. Three classes can be used to classify performance measurement functions, and one-modal measurement functions are suitable for evaluating the applicability of optimization algorithms because they have one optimum limit. The seven scalable unimodal benchmark functions $\{f_1 - f_7\}$. utilized in this investigation are displayed in Table (1). Multimodal benchmark functions. There are many locally optimal solutions for the high-dimensional multimodal functions. So optimization algorithms need to have a lot of exploring power. Table (2), lists the multimodal benchmarks $\{f_8 - f_{13}\}$. Small numbers of variables and local optimal solutions are present in the chosen fixed-dimensional multimodal functions. These issues test the optimization algorithms' capacity to locate the search space's primary optimal region. Table (3) shows fixed dimension multimodal$\{f_{14} - f_{23}\}$, These unimodal and multimodal functions of benchmarks are employed with (50) dimensions. And The iterations number is 100 iterations. The analysis has been performed on the MATLAB 2019 platform using PC an Intel Core i7, 1.8 GHz CPU and 16 GB of RAM.AND describes the parameters settings employed in the experimentation $\alpha = 5$, $C = 3$, $\lambda = 2, \mu = 3, \sigma = 0.5, \delta = 0.2$.

Table 1 Unimodal test functions.

function	Dimensions	Range
$f_1(\chi) = \sum_{i=1}^{m} \chi_i^2$	50	[-10,10]
$f_2(\chi) = \sum_{i=1}^{m} \lvert\chi_i\rvert + \prod_{i=1}^{m} \lvert\chi_i\rvert$	50	[-10,10]
$f_3(\chi) = \sum_{i=1}^{m} \left(\sum_{j=1}^{i} \chi_i \right)^2$	50	[-100,100]
$f_4(\chi) = \max\{ \lvert\chi_i\rvert, I \le i \le m\}$	50	[-12,12]
$f_5(\chi) \sum_{i=1}^{m-1} [100(\chi_{i+1} - \chi_i^2)^2 + (\chi_i - 1)^2]$	50	[-30,30]
$f_6(\chi) = \sum_{i=1}^{m} (\lvert\chi_i + 0.5\rvert)^2$	50	[-100,100]
$f_7(\chi) = \sum_{i=1}^{m} i\chi_i^4 + random(0,1)$	50	[-1,1]

Table 2 Multimodal test functions

function	Dimensions	Range
$f_8(\chi) = \sum_{i=1}^{m} -\chi_i \sin(\sqrt{\lvert\chi_i\rvert})$	50	$[-100,100]$
$f_9(\chi) = \sum_{i=1}^{m} [\chi_i^2 - 10\cos(2\pi\chi_i) + 10]$	50	$[-5.2,5.2]$
$f_{10}(\chi) = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n}\chi_i^2}\right) - \exp(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi\chi_i) + 20 + e$	50	$[-10,10]$
$f_{11}(\chi) = \frac{1}{4000}\sum_{i=1}^{n}\chi_i^2 - \prod_{i=1}^{n}\cos(\frac{\chi_i}{\sqrt{i}}) + 1$	50	$[-17,17]$
$f_{12}(\chi) = \frac{\pi}{m}\{10\sin(\pi y_i) + \sum_{i=1}^{m}(y_i - 1)^2 1 + 10sin^2(\pi y_{i+1})$ $+(y_i - 1)^2\} + \sum_{i=1}^{n} u(\chi_i, 10,100,4)$ $u(\chi_i, a, i,, n) = \begin{cases} k(\chi_i - a)^n, \chi_i > -a \\ 0 \quad , -a < \chi_i < a \\ k(-\chi_i - a)^n, \chi_i < -a \end{cases}$	50	$[-13,13]$
$f_{13}(\chi) = 0.1\{sin^2(3\pi\chi_m) + \sum_{i-1}^{m}(x_i - 1)^2[1 + sin^2(3\pi x_i + 1)] + (x_n - 1)^2[1 + sin^2(2\pi x_m)] + \sum_{i=1}^{m} u(\chi_i, 5,100,4)$	50	$[-50,50]$

Table 3 Fixed dimensional multimodal test functions

function	Dimensions	Range
$f_{14}(\chi) = \left(\frac{1}{500} + \sum_{j=1}^{25}\frac{1}{j + \sum_{i=1}^{2}(\chi_i - a_{ij})^6}\right)^{-1}$	2	$[-65.5,65.5]$
$f_{15}(\chi) = \sum_{i=1}^{11}\left[a_i - \frac{\chi_1 (b_i^2 + b_i \chi_2)}{b_i^2 + b_i \chi_3 + \chi_4}\right]^2$	4	$[-5,5]$
$f_{16}(\chi) = 4\chi_1^2 - 2.1\chi_1^4 + \frac{1}{3}\chi_1^6 + \chi_1\chi_2 - 4\chi_2^4 + 4\chi_2^4$	2	$[-5,5]$

$f_{17}(\chi) = \left(\chi_2 + \frac{5.1}{4\pi^2}\chi_1^2 + \frac{5}{\pi}\chi_1 - 6\right)^2 + 10\left(1 - \frac{1}{8\pi}\right)cos\chi_1 + 10$	2	$[-3,0] \times [9,12]$
$f_{18}(\chi) = [1 + (\chi_1 + \chi_2 + 1)^2(19 - 14\chi_1 + 3\chi_1^2 - 14\chi_2 + 6\chi_1\chi_2 + 3\chi_2^2)] \times [30 + (2\chi_1 - 3\chi_2)^2 \times (18 - 32\chi_1 + 12\chi_1^2 + 48\chi_2 - 36\chi_1 x_2 + 27\chi_2^2)]$	2	$[-2,2]$
$f_{19}(\chi) = -\sum_{i=1}^{4} c_i\, exp\left(-\sum_{j=1}^{3} aij\, \left(\chi_j - p_{ij}\right)^2\right)$	3	[0,1]
$f_{20}(\chi) = -\sum_{i=1}^{4} c_i\, exp\left(-\sum_{j=1}^{6} a_{ij}\, \left(\chi_j - p_{ij}\right)^2\right)$	6	[0,0.8]
$f_{21}(\chi) = -\sum_{i=1}^{5}[(\chi - a_i)(\chi - a_i)^T + 6c_i]^{-1}$	4	[0,9]
$f_{22}(\chi) = -\sum_{i=1}^{7}[(\chi - a_i)(\chi - a_i)^T + 6c_i]^{-1}$	4	[0,9]
$f_{23}(\chi) = -\sum_{i=1}^{10}[(\chi - a_i)(\chi - a_i)^T + 6c_i]^{-1}$	4	[0,9]

3.2 Statistical Experimental results and discussions

Employs statistical techniques to measure how well HBANM algorithm performs in various benchmark function classes. The standard deviation (SD) and the average depicts HBANM algorithm, average performance, while the standard deviation shows how stable this algorithm describes the parameters employed in the experimentation. The outcomes of the benchmark functions are the performance of the proposed algorithm for unimodal functions in a table (1) for multimodal functions in Table (2) and Fixed dimensional multimodal functions in table (3). The bold text in these tables highlights the best average results for each benchmark function. Table (4) findings demonstrate that the suggested HBANM algorithm improved outcomes for the unimodal test functions $\{f_1 - f_7\}$. These functions have a single global optimum rather than a local solution. The compared algorithms demonstrated that the HBANM algorithm outperformed the HBA algorithm for six unimodal testing functions and was equal in f_5. The table (5) Tested benchmark functions{ f_8– f_{13}} represent multimodal functions that include many local optima points. Evaluate the exploration capacity of optimization HBANM algorithm highly outperforms on HBA algorithm over five functions out of six except for the function. Table (6) show that HBANM algorithm performance over the tested fixed-dimension functions $\{f_{14}$– $f_{23}\}$,HBANM algorithm performs better when compared to HBA algorithm. Over seven functions out of ten and except $f_5$for the function equal $f_{18}$with HBA algorithm.

Table 4 Comparison Statistical results of HBANM and HBA algorithm on unimodal function

function	HBANM		HBA	
	ave	Std	ave	Std
f_8	**-3133.246468**	24.8978684	-1776.707635	338.78229
f_9	**4.502E-13**	2.59495E-12	3.67918E-07	3.60457E-06
f_{10}	**2.55553E-09**	2.53373E-09	6.84627E-08	9.83807E-08
f_{11}	1.60198E-10	1.58122E-09	**2.56429E-12**	2.0206E-11
f_{12}	**4.29869E-13**	3.18668E-12	0.248953411	0.06264011
f_{13}	**0.001959795**	0.010699411	3.696732149	0.403294749

$\varphi\emptyset$

Table 5 Comparison Statistical results of HBANM and HBA algorithm on unimodal function

function	HBANM		HBA	
	ave	Std	ave	Std
f_1	2.07104318	2.255926969	**1.251478568**	1.106952495
f_{15}	**0.002161407**	0.005562168	0.00396179	0.007696224
f_{16}	**-1.031628453**	1.37712E-15	-1.031628453	1.34362E-15
f_{17}	**0.46574603**	0.046791456	0.468002889	0.09257139
f_{18}	**3**	5.04724E-15	**3**	7.11075E-15
f_{19}	**-3.862782148**	6.75577E-15	-3.861048211	0.003281343
f_{20}	**-3.230444262**	0.137684809	-3.202178719	0.178736245
f_{21}	-9.259318641	2.098465848	**-9.468349161**	2.099234238
f_{22}	**-8.991391069**	2.662138359	-8.0456668	3.545917634
f_{23}	**-9.016906618**	2.920313223	-8.998252994	3.08812032

Table 6 Comparison Statistical results of HBANM and HBA algorithm on Fixed dimensional multimodal test functions

4. Application HBANM Algorithm in Allocation Reliability

Improving the reliability of a multi-objective system is essential due to its importance in the industry to design a highly reliable system by allocating increased component reliability, lower cost in this study system we get it from simplified modular Petri net of the shutdown system the detailed in [20], Conversion Petri nets, as a network is turned into a graph in this instance place are replaced with nodes, and the transitions and their connecting arcs are replaced with a single edge [16]. We get the network shown in figure (1). In this study, we calculate a complex network reliability in figure (1) by using Sum-of-disjoint Product [5].

$$
\begin{aligned}
R_s = \; & r_1r_2r_3 + r_1r_3r_4r_6 + r_1r_2r_8r_{10} + r_1r_4r_5r_{11} - r_1r_2r_3r_4r_6 + r_1r_3r_4r_5r_7 \\
& - r_1r_2r_3r_8r_{10} + r_1r_4r_6r_8r_{10} + r_1r_2r_8r_9r_{11} - r_1r_2r_3r_4r_5r_7 - r_1r_2r_3r_4r_5r_{11} \\
& - r_1r_3r_4r_5r_6r_7 - r_1r_3r_4r_5r_6r_{11} - r_1r_2r_4r_6r_8r_{10} - r_1r_3r_4r_5r_7r_{11} - r_1r_3r_4 \\
& r_6r_8r_{10} - r_1r_2r_3r_8r_9r_{11} + r_1r_4r_5r_7r_8r_{10} + r_1r_4r_6r_8r_9r_{11} - r_1r_2r_8r_9r_{10}r_{11} \\
& + r_1r_2r_3r_4r_5r_6r_7 + r_1r_2r_3r_4r_5r_6r_{11} + r_1r_2r_3r_4r_5r_7r_{11} + r_1r_2r_3r_4r_6r_8r_{10} - \\
& r_1r_2r_4r_5r_7r_8r_{10} + r_1r_3r_4r_5r_6r_7r_{11} - r_1r_3r_4r_5r_7r_8r_{10} - r_1r_2r_4r_5r_8r_9r_{11} - r_1 \\
& r_2r_4r_5r_8r_{10}r_{11} - r_1r_2r_4r_6r_8r_9r_{11} - r_1r_4r_5r_6r_7r_8r_{10} - r_1r_3r_4r_6r_8r_9r_{11} + r_1 \\
& r_2r_3r_8r_9r_{10}r_{11} + r_1r_4r_5r_6r_8r_9r_{11} - r_1r_4r_5r_7r_8r_{10}r_{11} - r_1r_4r_5r_6r_8r_{10}r_{11} - r_1 \\
& r_4r_6r_8r_9r_{10}r_{11} - r_1r_2r_3r_4r_5r_6r_7r_{11} + r_1r_2r_3r_4r_5r_7r_8r_{10} + r_1r_2r_3r_4r_5r_8r_9r_{11} \\
& + r_1r_2r_4r_5r_6r_7r_8r_{10} + r_1r_2r_3r_4r_5r_8r_{10}r_{11} + r_1r_2r_3r_4r_6r_8r_9r_{11} + r_1r_3r_4r_5r_6r_7 \\
& r_8r_{10} + r_1r_2r_4r_5r_6r_8r_9r_{11} + r_1r_2r_4r_5r_6r_8r_{10}r_{11} + r_1r_3r_4r_5r_6r_8r_9r_{10}r_{11} + r_1r_2 \\
& r_4r_5r_7r_8r_{10}r_{11} + r_1r_3r_4r_5r_6r_8r_{10}r_{11} + r_1r_3r_4r_5r_7r_8r_{10}r_{11} + r_1r_2r_4r_6r_8r_9r_{10}r_{11} \\
& + r_1r_2r_4r_6r_7r_8r_9r_{10}r_{11} + r_1r_3r_4r_6r_8r_9r_{10}r_{11} + r_1r_4r_5r_6r_7r_8r_{10}r_{11} + r_1r_4r_5r_6r_8 \\
& r_9r_{10}r_{11} - r_1r_2r_3r_4r_5r_6r_7r_8r_{10} - r_1r_2r_3r_4r_5r_6r_8r_9r_{11} - r_1r_2r_3r_4r_5r_6r_8r_{10}r_{11} - \\
& r_1r_2r_3r_4r_5r_7r_8r_{10}r_{11} - r_1r_2r_3r_4r_5r_8r_9r_{10}r_{11} - r_1r_2r_3r_4r_6r_8r_9r_{10}r_{11} - r_1r_2r_4r_5r_6 \\
& r_7r_8r_{10}r_{11} - r_1r_3r_4r_5r_6r_7r_8r_{10}r_{11} - r_1r_2r_4r_5r_6r_8r_9r_{10}r_{11} - r_1r_3r_4r_5r_6r_8r_9r_{10}r_{11} \\
& + r_1r_2r_3r_4r_5r_6r_7r_8r_{10}r_{11} + r_1r_2r_3r_4r_5r_6r_8r_9r_{10}r_{11} \qquad \ldots(13)
\end{aligned}
$$

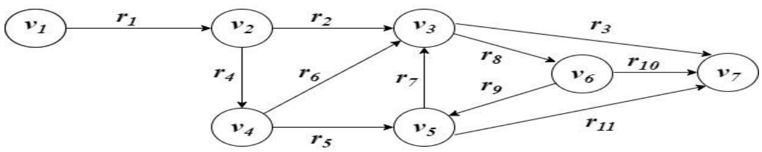

Fig. 1 network system

The following can be used to express the multi-objective problem [12,17]

$$\max R_s(r_i) \quad \text{for } i = 1,2,\ldots,11$$

$$\min C_s(r_i) = \sum_{i=1}^{11} a_i \left(\tan\left(\frac{\pi}{2}\, r_i\right)\right)^{\alpha_i}$$

subject to

$$0.95 \le R_s \le 0.99$$

$$0.7 \le r_i \le 0.99 \text{ for } i = 1,2,\ldots,11$$

Where $a = 0.0001, \alpha = 2 for\ i = 1,2,\ldots,11$

R_s represented by an equation (13) Multiple techniques can be used to solve problems involving multi-objective optimization. The weighted-sum approach reduces a multi-objective problem to a single-objective problem by giving weights to each function. The constraint handling is done via a penalty function [10].

$$\min f(r_i) = \mu_1\, C_s - \mu_2 R_s + \alpha\,(r_i)$$

Where $\mu_1 = \mu_2 = 0.5$ and $\alpha\,(r_i)$ is the penalty function

$$\alpha\,(r_i) = \alpha_1 \max(0, 0.99 - R_s) + \alpha_2 \max(0, R_s - 0.95)$$

Where α_1, α_2 is the penalty factor

find out the best reliability of a complex network by using HBANM algorithm and HBA algorithm

, we used The iterations number is (500) iterations describes the Parameters settings that were employed $\alpha = 1$, $C = 2$, $\lambda = 1, \beta = 2, \gamma = 0.5, \delta = 0.2$ The results were values of components reliability r_i and cost components C_i with best value of reliability network R_s and total cost C_s in table (7).

Table 7 Comparison HBANM and HBA for results value of r_i and C_i

Components	HBA		HBANM	
	Value of r_i	Value of C_i	Value of r_i	Value of C_i
r_1	0.9926	0.7400	0.9935	0.9592
r_2	0.9764	0.0727	0.9781	0.0844
r_3	0.9743	0.0613	0.9666	0.0363
r_4	0.9744	0.0618	0.9773	0.0786
r_5	0.9427	0.0123	0.9545	0.0195
r_6	0.9410	0.0116	0.9378	0.0104
r_7	0.8978	0.0038	0.8301	0.0013
r_8	0.9642	0.0316	0.9573	0.0222
r_9	0.7000	3.8518e-04	0.8654	0.0022
r_{10}	0.9634	0.0302	0.9454	0.0135
r_{11}	0.7000	3.8518e-04	0.9564	0.0213
Total	0.9913	1.0260	0.9927	1.2488

If we look at the values of a table (7), we can make the following observations: at values using an HBA algorithm are

$0.7000 \leq r_i \leq 0.9926$, for all *i = 1, 2,…,11*.

The highest value of r_i was for the first component, which is 0.9926, and the lowest value was for the component r_9, and r_{11} is 0.7000 and value of R_s is 0.9913and total cost C_s is 1.0260 , and values using the HBANM algorithm are

$00.8301 \leq r_i \leq 0.9935$, for all *i = 1,2,…,11.*

The highest value of r_i was for the first component, which is 0.9935, and the lowest value was for The seven component, and value of R_s is 0.9927 and total cost C_s is 1.2488 ,find that the results the HBANM algorithm for r_i and R_s have improved compared to the results we obtained from HBA algorithm.

5. Conclusions

This paper proposes a hybrid of the Honey Badger Algorithm (HBA) with the Nelder-Mead algorithm. Honey badger Nelder -Mead algorithm (HBANM) helps the proposed algorithm overcome the slow convergence of the standard by refining the best-obtained solution from the HBA algorithm. To verify the proposed algorithm's robustness and effectiveness, the HBANM algorithm has been applied to solve 23 problems. Its efficacy was investigated using statistical evaluation using the average and standard deviation. We found the

HBANM algorithm improved most of the functions compared to the results of the HBA algorithm. It applied the HBANM algorithm to a multi-objective reliability system in which reliability is maximized at as low a cost as possible. From the results, we find that the results have improved compared to the HBA algorithm.

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