

## Research Article

# Green Communication for Sixth-Generation Intent-Based Networks: An Architecture Based on Hybrid Computational Intelligence Algorithm

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The sixth-generation (6G) is envisioned as a pivotal technology that will support the ubiquitous seamless connectivity of substantial networks. The main advantage of 6G technology is leveraging Artificial Intelligence (AI) techniques for handling its interoperable functions. The pairing of 6G networks and AI creates new needs for infrastructure, data preparation, and governance. Thus, Intent-Based Network (IBN) architecture is a key infrastructure for 6G technology. Usually, these networks are formed of several clusters for data gathering from various heterogeneities in devices. Therefore, an important problem is to find the minimum transmission power for each node in the network clusters. This paper presents hybridization between two Computational Intelligence (CI) algorithms called the Marine Predator Algorithm and the Generalized Normal Distribution Optimization (MPGND). The proposed algorithm is applied to save power consumption which is an important problem in sustainable green 6G-IBN. MPGND is compared with several recently proposed algorithms, including Augmented Grey Wolf Optimizer (AGWO), Sine Tree-Seed Algorithm (STSA), Archimedes Optimization Algorithm (AOA), and Student Psychology-Based Optimization (SPBO). The experimental results with the statistical analysis demonstrate the merits and highly competitive performance of the proposed algorithm.

## 1. Introduction

The sixth-generation (6G) wireless network is the upcoming networking technology in many countries that will provide ubiquitous connectivity. This emerging technology is characterized by several features compared to the previous networking technologies such as holographic deep communication, Artificial Intelligence (AI), Visible Light Communication, 3D coverage frame, and ground and aerial wireless hotspots for cloud functionality [1]. One of the most influential of these features is the complete reliance on AI with its various technologies to control such a massive networking architecture. This has led to the emergence of the AI-empowered 6G or so-called Intent-Based Networks (IBNs) [2] in 6G technology.

IBN has been extracted from the well-known Software-Defined Network (SDN) as an emerging network infrastructure that poses a simple way for network administrators to achieve their intended goals [3]. Regarding 6G technology, pairing 6G with IBN architecture (6G-IBN) can offer optimization of the network efficiency. In particular, 6G-IBN is a technology that supports AI interference in the work of the network by collecting customer data and their requirements and autoconfiguring the network settings accordingly.

Several studies have been proposed for handling the problem of data manipulation in 6G-IBN and AI-empowered 6G architecture or in general networks' architecture. For instance, Zhang and Zhu [4] presented a comprehensive survey of the AI-empowered 6G. The roles of AI in 6G architecture were categorized into radio interface, traffic

control, security, management, and network optimization. The authors depicted that one of the main driving forces of enabling 6G with AI is lower energy consumption. In other words, the data burst from the ever-increasing number of small heterogeneous devices makes the power consumption of 6G particularly challenging, especially with the complexity of transceiver processing and the increase in end-user applications. Nawaz et al. [5] introduced a survey of potential usages of Quantum Machine Learning (QML) for the communication of 6G networks. The authors showed that handling the massive data traffic is a very difficult challenge for 6G technology because of high power consumption and the need for overhead security configurations. Zhou et al. [6] proposed a study of service-aware AI-empowered 6G. They mentioned that the efficient service of the 6G network depends on the collected information from end-users, even human sense information, including touch, smell, and taste, together with audio and visual data. Wei et al. [7] presented a study of the role of IBN in 6G technology. To our best knowledge, it is the only study that presents the IBN architecture for 6G technology. The authors showed that IBNs can continually learn and adapt to a changing network environment over time based on massive network data gathered in real time. So, 6G technology can exploit IBN architecture for an efficient communication experience.

From the previously discussed studies, it is clear that power-saving and data gathering are very imperative issues in AI-empowered 6G or 6G-IBN. In this paper, we proposed a hybrid Computational Intelligence (CI) algorithm for reducing energy consumption through the data gathering process in 6G-IBN. This problem is formulated as a minimization problem of single cluster transmission power [8], and ten different datasets have been solved. The experimental results and comparisons indicate the prosperity of the proposed algorithm. The remainder of the paper is organized as follows: Section 2 discusses the related works, Section 3 gives a definition of the regarded problem, Section 4 presents the proposed CI-based architecture, the experimental results are presented in Section 5, and finally, the conclusion is given in Section 6.

## 2. Related Works

This section discusses several examples of literature that handle the network clustering problem and the general efforts exerted for reducing energy consumption in networks. For instance, Xiao et al. [9] proposed an energy-efficient clustering scheme for Highway Addressable Remote Transducer (WirelessHART) networks. In the proposed Adaptive Free-shape Clustering (AFC) protocol, the area of interest was divided into several fan-shaped clusters. The nodes in each cluster challenge the positions of the Cell Node (CN), and the successful one modifies their coverages radius to adaptively cover the clusters with the minimum overlapped areas. By doing this, each fan-shaped cluster was divided again into several free-shape regions with respect to each CN's coverage, and the CN in each cluster was responsible for converge casting the data to the CH.

Rais et al. [10] introduced a Honeycomb Clustering Algorithm (EHCA) for energy-efficient honeycomb clustering.

EHCA was characterized by being a hierarchical and a geographical protocol at the same time. Moreover, the proposed algorithm guarantees changing the cluster head's location in each round. So, EHCA can balance the energy consumption in a given vertex of the honeycomb cluster.

Song et al. [11] presented a hybrid algorithm for efficient clustering and equalization routing of networks. In particular, the authors hybridized Particle Swarm Optimization (PSO) and Evolutionary Game Theory (EGT) algorithms for increasing the network lifetime. First, PSO was used for the selection of the CHs. After that, improved noncooperative evolutionary game theory was employed for a model building of the regarded energy waste problem caused by routing congestion.

Qureshi et al. [12] introduced the Gateway Clustering Energy-Efficient Centroid- (GCEEC-) based routing protocol for selecting the CH from the gateway nodes and centroid position. This assured that the gateway nodes reduce the data load from cluster head nodes and forward the data to the base station.

Pitchaimanickam and Murugaboopathi [13] combined the Firefly Algorithm (FA) with PSO for CH selection. The proposed algorithm was applied in the Centralized Low-Energy Adaptive Clustering Hierarchy (LEACH-C) which is an improved version of the Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol.

Ali et al. [14] proposed a novel ARSH-FATI-based Cluster Head Selection (ARSH-FATI-CHS) algorithm integrated with a heuristic called novel ranked-based clustering (NRC) for CH selection. Moreover, the proposed algorithm took into account the residual energy, communication distance parameters, and workload in the selection process.

Baradaran and Navi [15] presented a high-quality clustering algorithm (HQCA) for reducing the clustering error and the intercluster and intracluster distances. In particular, the authors used fuzzy logic for selecting CH with respect to several criteria, including the residual energy and the cluster minimum and maximum energy and distances between the nodes.

Mehmood and Aadil [16] introduced an efficient clustering using the Dragonfly Algorithm (DA). The proposed algorithm was applied in the health sector. In particular, the proposed algorithm reduced the power consumption of the Wireless Body Area Network (WBAN) with tiny healthcare monitoring devices.

Han et al. [17] proposed a clustering algorithm called CPEH for efficient clustering in the energy harvesting wireless sensor networks. In CPEH, the node's information was collected like the status of local energy, local density, and remote degree. Then, the collected information was used by fuzzy logic for the selection of cluster head and cluster size. Moreover, the Ant Colony Optimization (ACO) algorithm was used by CPEH for a highly efficient intercluster routing between cluster heads and the base station.

Regarding other efforts for energy saving of general networks, Di and Chen [18] proposed an Unmanned Aerial Vehicle- (UAV-) aided communication. In the proposed system, the drone first releases energy to a source and relay and then cooperatively transmitted the source and relayed information to their destination.

Zhu [19] presented an adaptive service mode mechanism based on online learning and a predictive method for an

evolving service migration dependent on a factor graph model. This model was proposed to solve the problem of placement of computing services at the edge computing side.

Nabavi et al. [20] proposed a multitarget greedy approach to find the optimal pathway in WSN to the near-optimal pathway. The proposed model was presented in this method to transfer the physical data of the sensor network to the base station for the desired applications.

Nguyen and Kha [21] studied the trade-offs between the energy and the spectral efficiency in the full-duplex (FD) multiuser multi-input multioutput (MU-MIMO) cloud radio access networks (CRANs).

Jiang et al. [22] proposed an improved problem formulation to maximize total output on the condition of ensuring fair productivity. In addition, a back-propagation-assisted full-duplex wireless communications network (FDMA-WPCN) with a two-way access point (FAP) and multiple wireless power-gathering devices (WDs) has been introduced.

### 3. Green 6G-IBN

**3.1. Problem Description.** One of the most important advanced applications of CI algorithms is the provisioning of 6G technology networks. As mentioned before, the technology of 6G-IBN is an emerging networking paradigm that ensures a fully connected wireless network by leveraging collected data from end-users (see Figure 1). Unfortunately, 6G consists of numerous terrestrial or nonterrestrial clusters in order to maximize the network lifetime. This issue makes the energy-efficient collection of such a massive data flood a very difficult challenge.

In the clustering paradigm, each node is connected at least with another node in the same cluster and the base station (directly or indirectly) [23]. Node connectivity is a significant issue that can help the network to be more reliable with regard to provision collecting of emitted data. The main objective of this paper is to find the minimum sum power of each node in a single cluster that ensures the full connection of all nodes. In this paper, the proposed algorithm is used for energy saving in 6G-IBN networks causing a sustainable green 6G network paradigm [24]. Next, the definition of the problem will be discussed.

**3.2. Mathematical Definition of the Problem.** Assume a single cluster with an indirect graph  $G$  of  $M$  nodes that are linked through indirect links  $\lambda$  such that  $G = (M, \lambda)$ . The main objective of all cluster nodes is to send their packets to a sink node which is responsible for the external retransmitting of collected data. A constant threshold of signal strength is  $\rho_{th}$  which is needed for reception and representation of the receiver sensitivity. In other words, the requirement of successful reception can be expressed as [25]

$$\omega_i - \beta(d_{ij}) \geq \rho_{th}, \quad (1)$$

where  $\omega_i$  is a power of a node  $i$  and  $\beta$  is a spatial increasing function of distance  $d_{ij}$  between two cluster nodes  $i$  and  $j$ . In general, this is true for free-space propagation and the same degradation of signals.

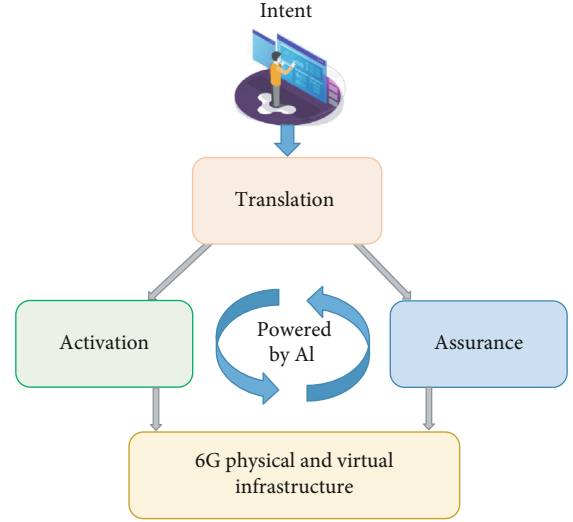


FIGURE 1: 6G-IBN architecture.

Thus, the transmitted power vector  $\vec{\omega}$  can be calculated by merging  $\beta$  and  $\omega$  as

$$\lambda_{ij}(\omega_i) = \begin{cases} 0, & \rho_{ij} < \rho_{th} \\ 1, & \rho_{ij} \geq \rho_{th} \end{cases} \quad \forall (i, j) \in \lambda, i = 1, 2, 3, \dots, M, \quad (2)$$

where  $\rho_{ij}$  is the level of received power at node  $j$  when node  $i$  has a transmitting power  $\omega_i$ .

The adequate connection happens when cluster node  $i$  has enough power that confirms that the received signal  $\rho_{ij}$  is greater than the receiver sensitivity  $\rho_{th}$ . In addition, the level of received power is a function that decreased with a proportion to the square distance  $d^2$  according to Friis formula [26]. This indicates that a cluster node can save more energy when it chooses shorter communication links. After all, the objective function of the regarded problem can be expressed as

$$\min Z = \sum_{i=1}^M \omega_i. \quad (3)$$

In other words, the main objective is to find the minimum power of transmission that ensures totally connected nodes in a single cluster.

Regarding the connectivity test of cluster nodes, it can be conducted by calculating the Laplacian matrix as [27]

$$\text{Lap} = \left( \gamma_{ij} \right)_{m \times m}, \quad (4)$$

$$\gamma_{ij} = \begin{cases} \text{deg}(m_i), & i = j, \\ -1, & i \neq j \text{ and } \lambda_{ij} = 1, \\ 0, & \text{otherwise,} \end{cases}$$

where  $\text{deg}(m_i)$  is the number of connected nodes to a cluster node  $m_i$ .

```

1: Set MPA parameters: itmax, n, FADs, P
2: Generate the preliminary population with a size n
3: while (it ≤ itmax) do
4:   Population evaluation
5:   Create the best solution matrix
6:   if(it < itmax/3)then
7:     Apply the first phase of searching
8:   elseif(itmax/3 < it < 2 * itmax/3)then
9:     Split the population of prey
10:    Apply the second searching phase
11:   else
12:     Apply the third searching phase
13:   endif
14:   FADs effect the population
15:   Update the best solution matrix
16: endwhile
17: return the top predator

```

ALGORITHM 1: MPA pseudocode.

```

1: Set GNDO parameters
2: Initialize the initial population
3: Evaluate each solution
4: Define the global best solution
5: while (it ≤ itmax) do
6:   if(O ≥ 0.5)then
7:     Compute the mean of the population
8:     Find  $a_i$ ,  $u_i$ , and  $b$ 
9:   else
10:    Find  $v_1$  and  $v_2$ 
11:    Apply the exploration phase
14:   endif
15: endwhile
16: return the best solution

```

ALGORITHM 2: GNDO pseudocode.

After the calculation of the Laplacian matrix, the Laplacian eigenvalue is calculated. If the second smallest eigenvalue of the Laplacian matrix is positive and there is at least one connection to a cluster node, then the single cluster nodes are verified to be fully connected.

## 4. Proposed Technique

*4.1. Marine Predator Algorithm.* The main inspiration of the Marine Predator Algorithm (MPA) [28] is the reciprocal action between predator and prey in the marine environment. This biological behavior is controlled by the behavior of Lévy and Brownian distribution. The MPA key hypotheses are as follows:

- (i) For environments with low intensity of prey, predators progress by the movement of Lévy; otherwise, they use the Brownian movement
- (ii) The percentages of the Lévy and Brownian movements are equal

```

1: Set MPA parameters: itmax, n, FADs, P
2: Generate the preliminary population with a size n
3: while (it ≤ itmax) do
4:   Population evaluation
5:   Create the best solution matrix
6:   if(it < itmax/3)then
7:     Apply the first phase of searching
8:   elseif(itmax/3 < it < 2 * itmax/3)then
9:     Split the population of prey
10:    Apply the second searching phase
11:   else
12:     Apply the third searching phase
13:   endif
14:   FADs effect the population
15:   Update the best solution matrix
16:   ifrand ≤ 0.2
17:     Compute the mean of prey population
18:     Find  $a_i$ ,  $u_i$ , and  $b$ 
19:     Apply GNDO exploitation phase
20:   endif
21: endwhile
22: return the best solution

```

ALGORITHM 3: MPGND pseudocode.

TABLE 1: Description of power saving datasets.

Parameter	Value
Range of transmission power	[-30, 0] dBm
Transmission frequency	915 MHz
Number of cluster nodes	20
Area of a single cluster	20 × 20 m
Receiver sensitivity	-60 dBm

- (iii) The predator behavior varies with respect to the factors of natural eddy formation or human-caused (FADs)
- (iv) A prey progress is either Brownian or Lévy while the predator uses Lévy's strategy with a low ratio of velocity ( $V = 0.1$ ) as its best choice
- (v) In the case of prey Lévy or Brownian movement with a high-velocity ratio, the predator stops moving
- (vi) The best movement behavior for a predator is not moving at all in the case when prey is moving either Brownian or Lévy with a high ratio of velocity ( $V ≥ 10$ ).
- (vii) At high velocity, the prey uses good memory to remind its partners and a good hunt site

MPA begins with generating an initial random population. The generated solutions are evaluated and ordered according to their fitness. After that, a matrix of best solutions or best predators is constructed. In particular, the matrix of best solutions contains clones of the best solution according to the population size. Also, this matrix is updated at the end of each search procedure.

The MPA searching mechanism depends on three key phases with respect to the ratio level of velocity. In the first

TABLE 2: Parameters of the compared algorithms of the energy-saving experiment.

Algorithm	Parameter	Value
MPA	Fish aggregating devices (FADs)	0.2
	$P$ constant	0.5
MPGND	Fish aggregating devices (FADs)	0.2
	$P$ constant	0.5
GNDO	Probability of GNDO's exploitation occurrence	0.2
	Switching probability $O$	0.5
STSA	Controlling parameter (ST)	0.6
	Switching probability	0.3
AOA	Constant $C_1$	1
	Constant $C_2$	6
	Constant $C_3$	1
	Constant $C_4$	2

third of the searching procedures, the predator does not move at all in the case when the prey is moving, either Brownian or Lévy, in the early stage of the search or at a high rate of velocity ( $V \geq 10$ ). This is achieved through the following:

$$\overrightarrow{\text{step}}_i = \overrightarrow{R}_B \otimes (\overrightarrow{\text{elite}}_i - \overrightarrow{R}_B \otimes \overrightarrow{\text{prey}}_i) \quad i = 1, 2, \dots, n, \quad (5)$$

$$\overrightarrow{\text{prey}}_i(t+1) = \overrightarrow{\text{prey}}_i(t) + P \cdot \overrightarrow{R} \otimes \overrightarrow{\text{step}}_i, \quad (6)$$

where  $\overrightarrow{\text{step}}_i$  is the step size of the prey,  $\overrightarrow{R}_B$  is a random vector derived from Brownian distribution, the notation  $\otimes$  means entry-wise multiplications,  $\overrightarrow{\text{elite}}_i$  is the finest solution from the matrix of best predators,  $\overrightarrow{\text{prey}}_i$  is the current candidate solution,  $P$  is a predefined constant value, and  $\overrightarrow{R}$  is a uniform random vector derived between  $[0, 1]$ .

In the second third of the searching procedures, a predator moves by Brownian strategy if a prey movement has a Lévy behavior with  $V = 1$ . In particular, the community of search agents is separated into two subgroups. The first half is updated by

$$\overrightarrow{\text{step}}_i = \overrightarrow{R}_L \otimes (\overrightarrow{\text{elite}}_i - \overrightarrow{R}_L \otimes \overrightarrow{\text{prey}}_i) \quad i = 1, 2, \dots, \frac{n}{3}, \quad (7)$$

$$\overrightarrow{\text{prey}}_i(t+1) = \overrightarrow{\text{prey}}_i(t) + P \cdot \overrightarrow{R} \otimes \overrightarrow{\text{step}}_i, \quad (8)$$

where  $\overrightarrow{R}_L$  is a Lévy random vector.

The second half is calculated as the following:

$$\overrightarrow{\text{step}}_i = \overrightarrow{R}_B \otimes (\overrightarrow{R}_B \otimes \overrightarrow{\text{elite}}_i - \overrightarrow{\text{prey}}_i) \quad i = \frac{n}{2} + 1, \dots, n, \quad (9)$$

$$\overrightarrow{\text{prey}}_i(t+1) = \overrightarrow{\text{elite}}_i + P \cdot C \otimes \overrightarrow{\text{step}}_i, \quad (10)$$

where  $C$  is an adaptive parameter that can be computed as

$$C = \left(1 - \frac{\text{it}}{\text{itmax}}\right)^{(2 * (\text{it}/\text{itmax}))}, \quad (11)$$

where it is the current search iteration and itmax is the total iteration number.

In the last third of the searching procedures, a predator moves by Lévy's strategy with a low velocity ( $V = 0.1$ ) if prey progresses in either Brownian or Lévy behavior. The next solution is computed as

$$\overrightarrow{\text{step}}_i = \overrightarrow{R}_L \otimes (\overrightarrow{R}_L \otimes \overrightarrow{\text{elite}}_i - \overrightarrow{\text{prey}}_i) \quad i = 1, 2, \dots, n, \quad (12)$$

$$\overrightarrow{\text{prey}}_i(t+1) = \overrightarrow{\text{elite}}_i + P \cdot C \otimes \overrightarrow{\text{step}}_i. \quad (13)$$

For a natural eddy formation or FADs, an additional searching phase is added. This condition occurs based on a predetermined probability (FADs = 0.2). Then, the calculation of the next candidate solutions will be as follows:

$$\overrightarrow{\text{prey}}_i(t+1) = \begin{cases} \overrightarrow{\text{prey}}_i(t) + C \left[ \overrightarrow{\text{lb}} + \overrightarrow{R} \otimes (\overrightarrow{\text{ub}} - \overrightarrow{\text{lb}}) \right] \otimes \overrightarrow{U}, & \text{if rand} \leq \text{FADs}, \\ \overrightarrow{\text{prey}}_i(t) + [\text{FADs}(1 - \text{rand}) + \text{rand}] (\overrightarrow{\text{prey}}_{r1} - \overrightarrow{\text{prey}}_{r2}), & \text{otherwise,} \end{cases} \quad (14)$$

TABLE 3: Descriptive statistics of ten energy-saving datasets for 30 independent runs.

Dataset	Algorithms	Minimum	Maximum	Mean	Std. deviation	<i>p</i> value
Dataset 1	MPGND	-5.0353	-4.6055	-4.971799	0.0842245	0.3725
	MPA	-5.0390	0.8748	-4.736040	1.0733152	
	GNDO	-4.6940	NA	NA	NA	
	STSA	1.3867	3.8049	2.992732	1.0432979	
	AGWO	4.3612	8.0487	6.250986	0.5431646	
	AOA	11.4291	13.0103	12.871480	0.4258639	
	SPBO	5.7984	NA	NA	NA	
Dataset 2	MPGND	-7.6795	-7.4268	-7.619333	0.0533462	1.7219e-37
	MPA	-7.6737	-7.4363	-7.609363	0.0558062	
	GNDO	-7.4016	-5.7387	-6.630076	0.4245837	
	STSA	1.2987	3.4476	2.483630	0.6018840	
	AGWO	-1.3547	8.6427	5.120709	2.5246429	
	AOA	4.9608	13.0103	11.540879	2.8188932	
	SPBO	4.3756	NA	NA	NA	
Dataset 3	MPGND	-5.0329	-4.7821	-4.963054	0.0604851	2.6711e-56
	MPA	-5.0320	-3.0296	-4.847741	0.4636465	
	GNDO	-4.5856	2.4853	-2.941780	1.5729501	
	STSA	1.5981	4.1361	2.982084	0.5763874	
	AGWO	2.5864	8.6388	5.628007	1.3833722	
	AOA	11.0271	13.0103	12.856682	0.4839176	
	SPBO	5.6385	NA	NA	NA	
Dataset 4	MPGND	-6.2499	-6.0708	-6.204747	0.0415812	2.14592e-22
	MPA	-6.2479	-5.3300	-6.170170	0.1623287	
	GNDO	-6.0514	-4.8293	-5.483168	0.2581445	
	STSA	0.9636	3.8398	2.291970	0.6265332	
	AGWO	-1.1276	8.0590	5.280250	2.2070198	
	AOA	4.8001	13.0103	11.756545	2.5926190	
	SPBO	1.8805	NA	NA	NA	
Dataset 5	MPGND	-7.6628	-6.0328	-7.556524	0.2927583	2.6711e-56
	MPA	-7.6702	-7.4857	-7.612344	0.0424757	
	GNDO	-7.5239	-5.6587	-6.490170	0.5304868	
	STSA	1.2061	3.6150	2.448804	0.6424697	
	AGWO	-1.4115	7.3641	4.897111	2.3316796	
	AOA	4.0457	13.0103	11.979176	2.7014299	
	SPBO	4.8835	NA	NA	NA	
Dataset 6	MPGND	-6.2420	-6.0254	-6.194883	0.0454856	6.4893e-20
	MPA	-6.2520	-6.0199	-6.204955	0.0499140	
	GNDO	-5.9981	NA	NA	NA	
	STSA	1.1007	3.1314	2.295611	0.4713219	
	AGWO	-0.0141	7.3384	4.697782	1.8008367	
	AOA	3.5555	13.0103	12.076295	2.4419530	
	SPBO	4.2507	NA	NA	NA	
Dataset 7	MPGND	-5.0351	-4.8050	-4.960284	0.0533460	4.437e-60
	MPA	-5.0304	-0.0620	-4.783209	0.8989318	
	GNDO	-3.1342	NA	NA	NA	
	STSA	2.0232	3.9566	3.178077	0.4732431	
	AGWO	2.9210	8.1577	6.284094	1.2189823	
	AOA	11.3516	13.0103	12.862974	0.4515585	

TABLE 3: Continued.

Dataset	Algorithms	Minimum	Maximum	Mean	Std. deviation	$p$ value
Dataset 8	SPBO	8.0443	NA	NA	NA	6.1764e-34
	MPGND	-7.2786	-6.6134	-7.193837	0.1233936	
	MPA	-7.2788	-5.2792	-7.123229	0.3626609	
	GNDO	-6.7108	-4.0510	-5.853400	0.6097682	
	STSA	1.2895	3.1327	2.495311	0.4558036	
	AGWO	-0.7610	8.5611	4.841022	2.6100941	
	AOA	4.6395	13.0103	12.350321	1.8322584	
	SPBO	4.8479	NA	NA	NA	
Dataset 9	MPGND	-5.0368	-4.4658	-4.917226	0.1478834	6.44134e-53
	MPA	-5.0352	-2.5880	-4.848956	0.4633953	
	GNDO	-3.8810	NA	NA	NA	
	STSA	2.2282	4.3081	3.394901	0.4834886	
	AGWO	4.5580	8.1604	6.515027	0.8505038	
	AOA	11.8462	13.0103	12.971496	0.2125355	
	SPBO	7.6914	NA	NA	NA	
	MPGND	-4.4953	-4.1923	-4.420555	0.0832273	
Dataset 10	MPA	-4.4941	-3.1240	-4.359911	0.2772618	4.4372e-60
	GNDO	-3.8503	NA	NA	NA	
	STSA	1.8189	4.2035	3.407594	0.5210286	
	AGWO	3.0609	8.7888	6.390348	1.5931690	
	AOA	11.4886	13.0103	12.823781	0.4858622	
	SPBO	6.5527	NA	NA	NA	

NA: not a number.

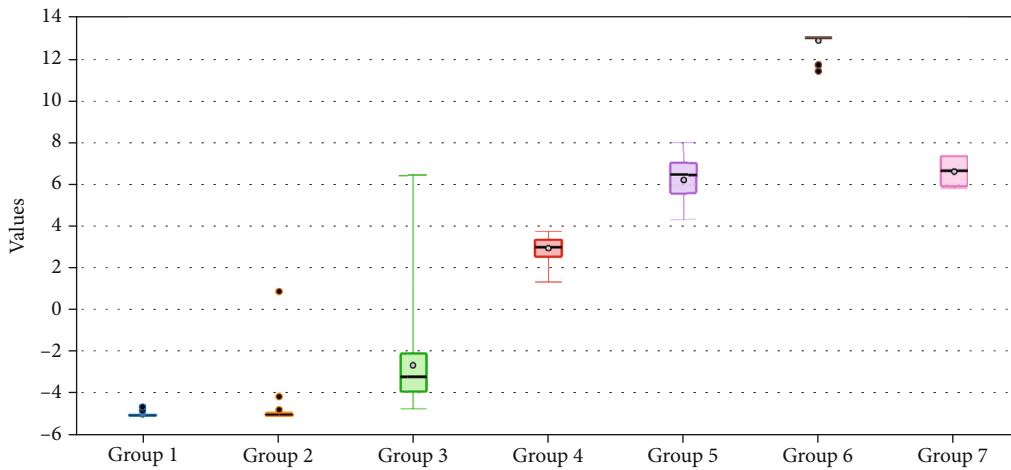


FIGURE 2: The box plot of dataset 1.

where  $\vec{lb}$  and  $\vec{ub}$  are the searching area lower and upper bound vectors, respectively;  $\vec{U}$  is a random binary vector;  $\text{rand}$  is a uniform random value derived between  $[0, 1]$ ; and  $\vec{\text{prey}}_{r_1}$  and  $\vec{\text{prey}}_{r_2}$  are two randomly selected solutions. The MPA pseudocode is presented in Algorithm 1.

**4.2. Generalized Normal Distribution Optimization.** The Generalized Normal Distribution Optimization (GNDO)

algorithm [29] emulates the model of a generalized normal distribution or so-called Gaussian distribution. In particular, each search agent updates its position according to a generalized normal distribution curve. The searching process begins with the initialization of random search agents. Then, the whole population is evaluated in order to determine the current global best solution. After that, the searching behavior is determined according to a predefined probability  $O$ . In other words, if a random number is bigger than  $O$ , then the

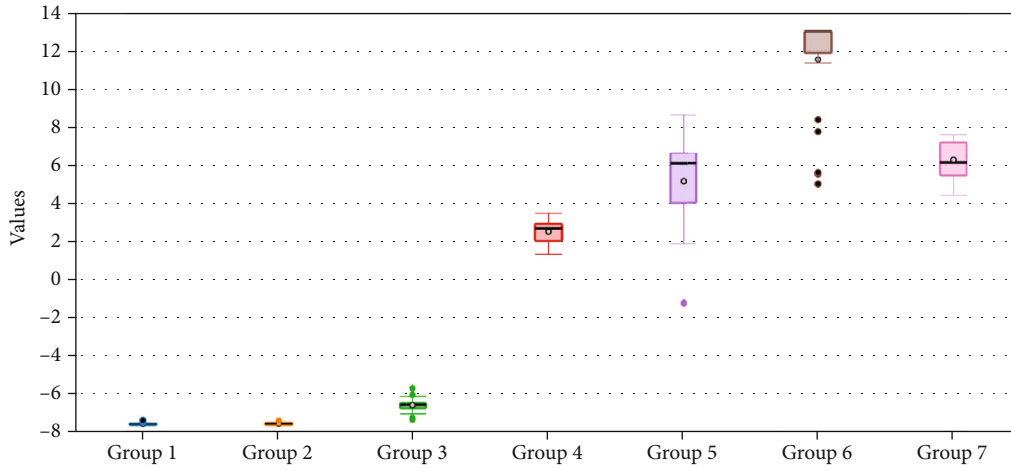


FIGURE 3: The box plot of dataset 2.

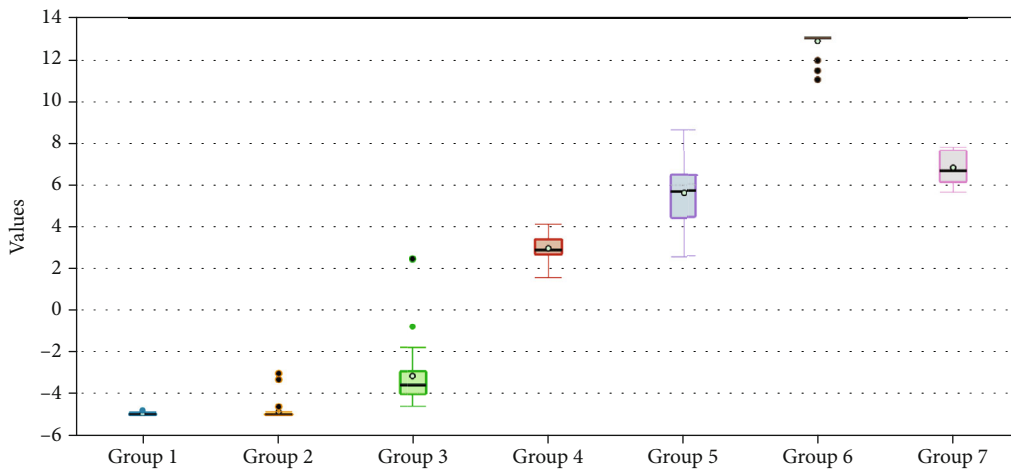


FIGURE 4: The box plot of dataset 3.

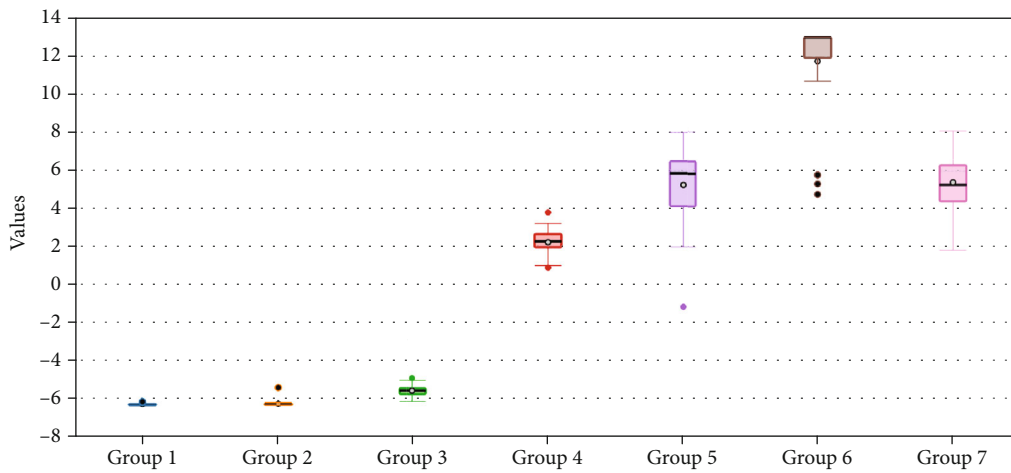


FIGURE 5: The box plot of dataset 4.



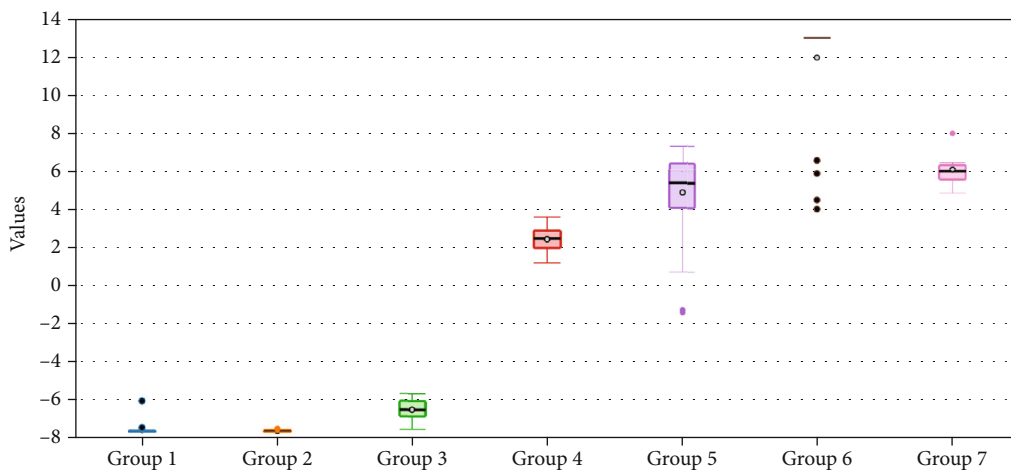


FIGURE 6: The box plot of dataset 5.

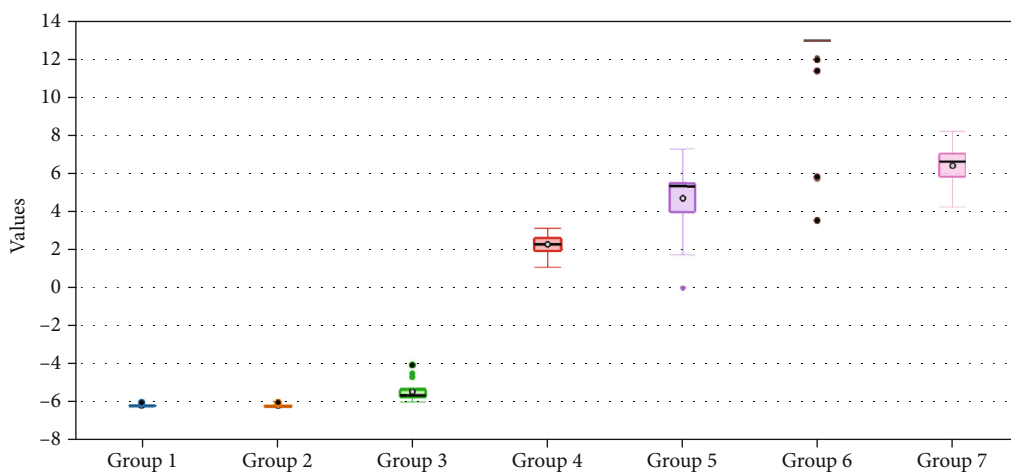


FIGURE 7: The box plot of dataset 6.

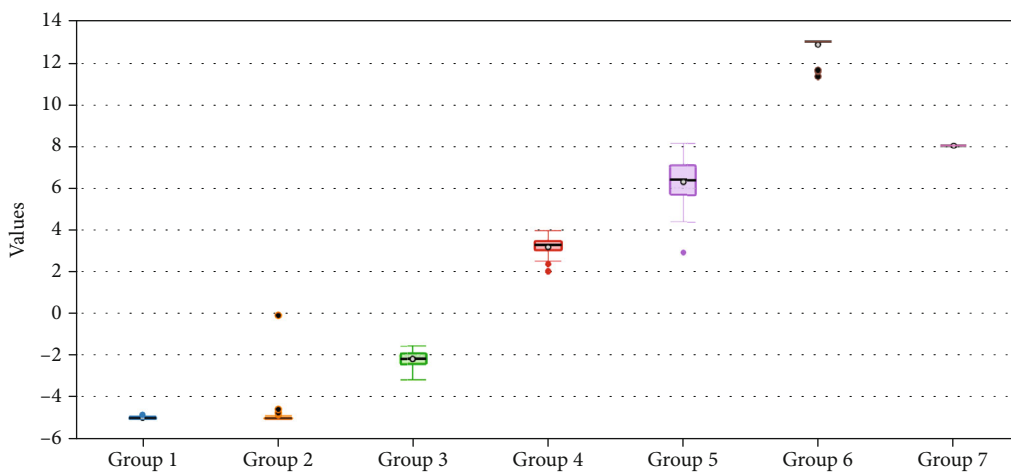


FIGURE 8: The box plot of dataset 7.

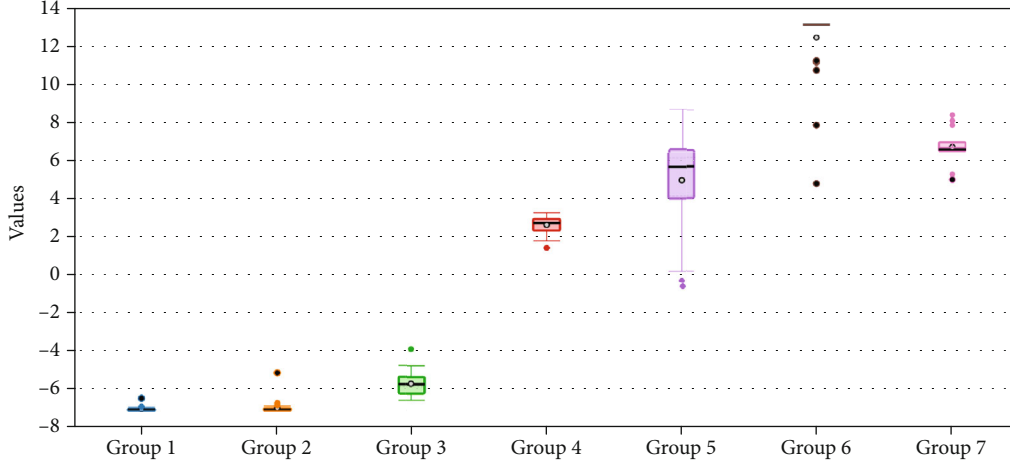


FIGURE 9: The box plot of dataset 8.

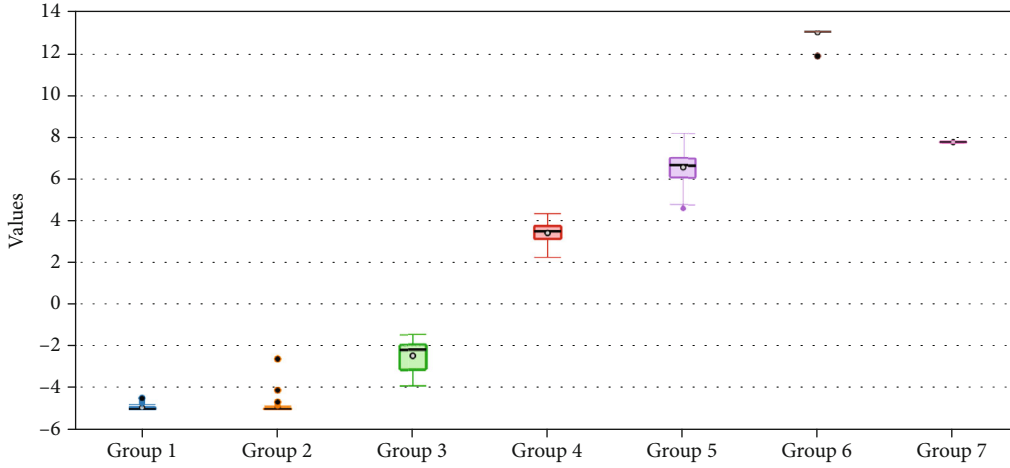


FIGURE 10: The box plot of dataset 9.

exploitation phase is performed. First, the mean value of the whole population is calculated. After that, the next solution is computed as

$$x_{i+1} = a_i + u_i \times b, \quad i = 1, 2, \dots, n, \quad (15)$$

where  $x_{i+1}$  is the next candidate solution. The other parameters  $a_i$ ,  $u_i$ , and  $b$  can be defined as

$$a_i = \frac{1}{3}(x_i + x_i^* + m), \quad (16)$$

$$u_i = \sqrt{\frac{1}{3}[(x_i - a_i)^2 + (x_i^* - a_i)^2 + (m - a_i)^2]}, \quad (17)$$

$$b = \begin{cases} \sqrt{-\log(r_1)} \times \cos(2\pi r_2), & r_3 \leq r_4, \\ \sqrt{-\log(r_1)} \times \cos(2\pi r_2 + \pi), & \text{otherwise,} \end{cases} \quad (18)$$

where  $x_i$  is the current candidate solution,  $x_i^*$  is the global best solution, and  $m$  is the mean of the current population.

The parameters  $r_1$ ,  $r_2$ ,  $r_3$ , and  $r_4$  are uniform random numbers between  $[0, 1]$ .

On the other hand, the exploration phase is applied by computing the next candidate solution as

$$x_{i+1} = x_i + r_5 \times (|\text{rn}_1| \times v_1) + (1 - r_5) \times (|\text{rn}_2| \times v_2), \quad i = 1, 2, \dots, n, \quad (19)$$

where  $r_5$  is a uniform random number between  $[0, 1]$ . The parameters  $\text{rn}_1$  and  $\text{rn}_2$  are random numbers selected from a normal distribution between  $[0, 1]$ , whereas the parameters  $v_1$  and  $v_2$  can be computed as

$$v_1 = \begin{cases} x_i - x_{r_1}, & \text{if } f(x_i) < f(x_{r_1}), \\ x_{r_1} - x_i, & \text{otherwise,} \end{cases} \quad (20)$$

$$v_2 = \begin{cases} x_{r_2} - x_{r_3}, & \text{if } f(x_{r_2}) < f(x_{r_3}), \\ x_{r_3} - x_{r_2}, & \text{otherwise,} \end{cases} \quad (21)$$

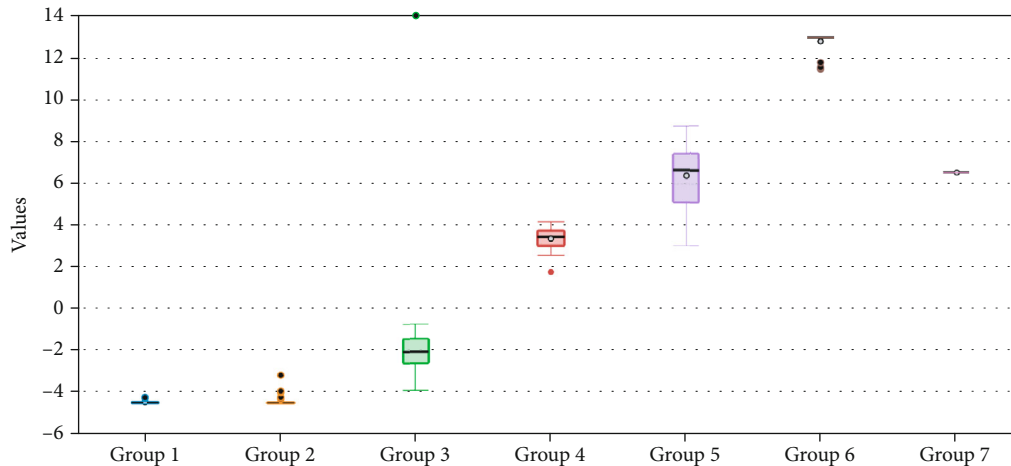


FIGURE 11: The box plot of dataset 10.

where  $x_{r1}$ ,  $x_{r2}$ , and  $x_{r3}$  are different randomly selected solutions from the current population. Algorithm 2 shows the GNDO pseudocode.

**4.3. Proposed Hybrid CI Algorithm.** In this paper, the original MPA is a hybrid with the GNDO's exploitation phase. The pseudocode of the proposed hybrid algorithm (MPGND) is presented in Algorithm 3.

## 5. Experimental Results

In this section, the proposed algorithm is applied to solve the problem of a single cluster power saving. The ten experiment datasets are obtained from [30], whereas the characteristics of the selected datasets are presented in Table 1. In this experiment, MPGND is compared with many metaheuristics, including the original MPA, GNDO, Augmented Grey Wolf Optimizer (AGWO) [31], Sine Tree-Seed Algorithm (STSA) [32], Archimedes Optimization Algorithm (AOA) [33], and Student Psychology-Based Optimization (SPBO) [34] algorithm. The number of total search iterations of all algorithms is set to 500 while the population size is set to 30. The other parameters of the compared algorithms are given in Table 2. The descriptive statistics of MPGND and the compared algorithms after 30 independent runs are exposed in Table 3. As observed, MPGND significantly outperforms the other algorithms in minimizing the sum of the transmission power of cluster nodes. In addition, it is able to reach a feasible solution compared to the other algorithms. For analyzing the performance of MPGND and the comparators, the one-way ANOVA test [35] is performed with a significant value equal to 0.05. As shown in Figures 2–11, MPGND is better than the other algorithms. This indicates that the MPGND-obtained transmission power values are lower than those of the other comparators.

## 6. Conclusion

6G-IBN or the AI-empowered 6G network mainly depends on the efficiency of the data collection process. In this paper,

the MPGND algorithm is introduced for a power-efficient collection of user information in IBN. The proposed algorithm is compared with several other algorithms on ten different datasets. From the comparison with the original MPA, the final obtained results of MPGND are better than MPA because of the additional exploitation phase. Although the difference between the solutions of MPA and MPGND appears very small, the difference becomes significant with the increment of the cluster numbers. In addition, the proposed algorithm is significantly better than the other comparators for the ten datasets.

For future works, we suggest using the proposed algorithm for solving other 6G-related problems such as scheduling, coverage, and security. Also, it is suggested to use the proposed algorithm for solving the regarded problem with the increment of the number of clusters.

## Data Availability

The benchmark case studies, experiment results, and any other data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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