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Dual-discriminator Conditional Generative Adversarial Network Optimized with Hybrid Momentum Search Algorithm and Giza Pyramids Construction Algorithm for Cluster-based Routing in WSN Assisted IoT

Darshan B. D.*
Department of Electronics and Communication Engineering, S J B Institute of Technology, Kengeri, Bengaluru-560060, Karnataka, India
E-mail: darshan156@gmail.com
ORCID iD: https://orcid.org/0000-0003-4674-4139

Prashanth C. R.
Department of Electronics & Telecommunication Engineering, Dr. Ambedkar Institute of Technology, Bengaluru-560056, Karnataka, India
E-mail: prashanthcr.et@drait.edu.in
ORCID iD: https://orcid.org/0009-0002-8590-4385

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Abstract: Wireless sensor network (WSN) efficiently sends and receives the data on the internet of things (IoT) environment. As a large-scale WSN's nodes are powered by batteries, it is essential to create an energy-efficient system to decrease energy consumption and increase the network's lifespan. The existing methods not present effectual cluster head (CH) selection and trust node computation. Therefore, dual-discriminator conditional generative adversarial network optimized with a hybrid Momentum search algorithm and Giza Pyramids Construction algorithm for Cluster-Based Routing in WSN Assisted IoT is proposed in this manuscript, for securing data transmission by identifying the optimum CH in the network (DDcGAN-MSA-GPCA-CBR-WSN-IoT). Initially, the proposed method is acting routing process via cluster head. Therefore, Dual-Discriminator conditional Generative Adversarial Network (DDcGAN) is considered to select the CH depending on multi-objective fitness function. The multi-objective fitness function, such as energy, delay, throughput, distance among the nodes, cluster density, capacity, collision, traffic rate, and cluster density. Based on fitness function, CH is selected. After cluster head selection, a malicious node depends on three parameters: trust, delay, and distance. These three parameters are optimized by hyb MSA-GPCA for ideal trust path selection. The proposed DDcGAN-MSA-GPCA-WSN-IoT technique is activated in PYTHON and network simulator (NS2) tool. Its effectiveness is analyzed under performance metrics, such as number of alive nodes, dead nodes, delay, energy consumption, packet delivery ratio, a lifetime of sensor nodes, and total residual energy. The simulation outcomes display that the proposed method attains lower delay, higher packet delivery ratio and high network lifetime when comparing to the existing models.

Index Terms: Cluster-Based Routing, Clustering Process, Dual-Discriminator Conditional Generative Adversarial Network, Hybrid Momentum Search Algorithm, Giza Pyramids Construction Algorithm, Cluster Head Selection.

1. Introduction

Nowadays, WSNs are utilized globally for plenty of purposes. Modern Micro-electro-mechanical Systems advancements are integrated with wireless network to create more compact, power-efficient distributed devices that can process both local and wireless communication [1-3], known as sensor nodes. Working with sensors reduces human effort and supports research in many areas, including observation, home secure, healthcare, industrial tracking, and military operations [4,5]. To effectively distribute the sensors existence for the scope of a certain mission, it is vital to manage the energy [6]. Due to the depletion of energy, failures in sensor networks are also increasing [7]. After some time, a specific portion of the network experiences energy embarrassment and eventually quits operating [8]. Sensor node's fault causes connectivity loss and increase network lifetime [9]. At clustered networks, it makes holes in network topology and divides the clusters by creating the losses of connectivity and data [10].

Clustering is a proficient energy conservation method in WSNs [11]. Sensor nodes are collected into clusters and cluster heads (CH) designates to each cluster [12]. CH is responsible for distribution and task allocation to the cluster member [13]. A routing algorithm lessens the energy usage rate and raises the lifespan of networks after clustering. Therefore, the optimal utilization of extraordinary and scarce resources is in demand of WSNs. WSN cluster collects high amount of cluster with a drop node. Every cluster contains cluster members including cluster heads [14]. CH is a significant role for cluster base WSN that leads whole cluster members. So, CH selection is vital for processing a cluster-based wireless sensor network. CH contains the capacity of sending and receiving the data to the base station (BS) [15]. Malicious nodes can enter the network and infect it if there is no registration and verification procedure in place for network node [16-18]. That's why trust path computation is significant to prevent the network from spiteful node [19,20]. The sensor nodes collect the information from the context and feed it to CH. The CH derives the data then gives it for security purposes.

The existing CH selection and routing algorithms reduce energy consumption by averting data, bandwidth, and memory redundancy. It has a trade-off among the level of security, and energy consumption, because the high level of security contains more intensive computational functions and vice versa [21-32]. There is no need to upgrade the solutions obtained so far. Recently, deep learning-based optimization strategies have opened new ways of solving routing issues [21-32]. This motivated me to research this work.

This manuscript proposes a DDcGAN-MSA-GPCA-CBR-WSN-IoT for securing data transmission through identifying ideal CHs at the network. Initially, DDcGAN select the cluster head precisely. After the selection of cluster head, the optimal path is necessary to transmit the data safely. Hence, the hybrid Momentum search algorithm and Giza Pyramids Construction algorithm hyb (MSA-GPCA) are utilized to achieve the optimum path.

The main contributions of this manuscript are abridged below,

- DDcGAN optimized with hyb MSA-GPCA for cluster-Based Routing in WSN Assisted IoT (DDcGAN-MSA-GPCA-CBR-WSN-IoT**)** is proposed.
- The proposed method contains two phases, Phase (1) and phase (1). Cluster head selection is done in phase (1), and optimal path selection is done in phase (2).
- Initially, the proposed method carried out the routing process via cluster heads. Therefore, DDcGAN is used to select the CH depending on multiple objective fitness function [33].
- The multiple objective fitness function, such as energy, delay, throughput, the distance among the nodes, cluster density, capacity, collision, traffic rate, cluster density is considered. Based on the fitness function, CH is selected with the help of DDcGAN.
- After the cluster head selection, a malicious node attains in the cluster. Hence hyb MSA-GPCA [34,35] approach provides end-to-end confidentiality and integrity.
- The optimal path is selected based on three parameters: trust, delay, and distance. These 3 parameters are optimized under hyb MSA-GPCA method for ideal trust path selection. At last, the optimum trust path transfers the data to the base station.
- The efficacy of the proposed approach is assessed with performance metrics, such as number of alive nodes, dead nodes, delay, energy consumption, PDR, a lifetime of sensor nodes, and total residual energy.
- The performance of the proposed DDcGAN-MSA-GPCA-CBR-WSN-IoT work is compared with existing models, like deep belief network (DBN) and Mantaray Foraging Optimization (MRFO) algorithm for Cluster-based Routing in WSN Assisted internet of things (DBN-MRFO-CBR-WSN-IoT)[21], Grey wolf optimizer for Cluster-based Routing in WSN Assisted (GWO-CBR-WSN-IoT) [22], black widow optimization (BWO) for Cluster-Based Routing in WSN Assisted IoT (BWO-CBR-WSN-IoT)[23], and particle swarm optimization technique for Cluster-Based Routing in WSN Assisted IoT (PSO-CBR-WSN-IoT) [24].

The rest of this manuscript is designed as: the literature survey is portrayed in section 2, the proposed methodology is described in section 3, the result with discussion is proved in section 4, conclusion is depicted in section 5.

2. Related Works

Numerous studies were suggested in the literature related to Cluster-Based Routing in IoT-assisted WSNs. Certain recent works are discussed here,

Arya [21] have presented a Deep Belief Network fed routing protocol for effective data communication in the wireless sensor network. Firstly, the entire network node was clustered as clusters by means of a Reinforcement Learning (RL) algorithm that allocates compensation for the nodes that fit into the specific cluster. Then, the CH for effective data transmission was carefully chosen with the help of Mantaray Foraging Optimization. The suggested model attained feasible network lifespan with high delay.

Agrawal et al., [22] have presented a Grey Wolf Optimizer-based clustering scheme for wireless sensor networks. The aim was to increase the networks lifespan for CH selection. For the attainment of this assignment, a Grey Wolf Optimizer (GWO) was deemed. The general GWO was enhanced to present the explicit persistence of cluster head selection. The suggested method attains improved PDR with high energy consumption.

Vaiyapuri et al., [23] have suggested CH selection and optimal path selection using Black Widow Optimization (BWO) with an Oppositional Artificial Bee Colony (OABC) in WSN. In IoT-assisted WSN, a huge number of information was gathered that causes several issues such as delay and less throughput. To resolve this limitation, the clustering method was suggested. This BWO algorithm was applied for efficient CH selection. After CH selection, some malicious nodes arrived on the network. Hence OABC algorithm was suggested to select the optimal path.

Loganathan and Arumugam [24] have suggested energy-efficient clustering approach depending upon particle swarm optimization for WSN. Initially, CHs were arbitrarily chosen in each section and were not thought to be an efficient use of energy. The sink node deems Particle Swarm Optimization method to select the cluster head in every section capably. The selected CH node formulates the original cluster. Distance from a sink, sensor nodes remaining energy, CH to the members were agreed to choose the CH in the sensor node.

Agbulu et al., [25] have presented a PECDF-CMRP method for cluster-based routing in IoT-assisted WSN. Initially, the K-means algorithm was modified to allocate the nodes in unsatisfactory cells. CH was preferred by multi-objective fitness functions. Then relay nodes were selected through K cells to create supportive networks for data transmission from the result segments to the central gateway. The relay allotment was expressed as extension problems about node's energy with a malicious path. The data collection was recognized by single-level wavelet sparsity-base fusion. The outcomes display lower delay and energy consumption with less network lifespan.

Juneja [26] have presented a FACO for cluster-base routing in IoT-assisted WSN. The load analysis was attained when developing the clusters. The topic concerned probability vectors. Ant colony optimization (ACO) was an effective method for achieving cluster-base hierarchical routing along 2 level communications when the clusters designed. To account for degree consideration and energy, node-to-CH connections were first enabled. For inter-cluster route formation, a fuzzy-incorporated ant colony optimization was employed. It attains less energy efficiency.

Malisetti and Pamula [27] has presented an ML-AEFA and CGWO method based Energy effective CH routing in WSN. The suggested method has two phases: CH selection along optimal path selection. In phase 1, Moth Levy adopted Artificial Electric Field Algorithm suggested for efficient CH selection. The CH selection depends on node energy, node distance, node density, and traffic rate. After the CH selection, the mischievous path was arrived; hence Customized Grey Wolf Optimization algorithm was suggested to choose the optimum path from the mischievous path. Finally, the secure transmission was achieved. Lastly, the presentation of the suggested method was likened to the existing methods. The performance of the suggested method attains a high network lifetime with less node reliability.

Sharma et al., [28] have presented energy-efficient TMFO/GA-based CH selection in WSNs. In clustered WSN framework, by using moth flame optimization, the selection of the most deserving trustworthy head node was completed. On the basis of five significant constraints, including the average cluster distance, average transmission delay, connected node density, direct trust metrics like progressing the packet forwarding, and residual energy for the elected node fitness function in TMFO/GA were evaluated.

Kaur et al., [29] have presented a DRL-based routing method in WSN. The suggested method uses the Deep-Reinforcement-Learning (DRL) method that decreases the delay and raises the network lifespan. The suggested model splits the entire network into dissimilar imbalanced clusters based on the existing data load presented in the sensor node that expressively stops network loss. The suggested method was achieved by ns3. The investigational outcomes are likened to the existing method to reveal the efficacy of the suggested method by means of the count of alive nodes, PDR, and EE, with high network delay.

Shyjith et al., [30] have presented a dynamic selection of cluster heads using energy efficient routing protocol in WSN. For the cluster head selection, a hybrid optimization approach was presented. The presented cluster head selection encompasses 3 phases: setup, transmission, and measurement. Initially, the node's mobility with energy was modified. The setup phase was administered by selecting a cluster head utilizing optimized sleep-awake energy-efficient distributed clustering that defined the optimum threshold and cluster head using the presented rider-cat swarm optimization algorithm. By using multiple objective constraints, the threshold along CH was selected. Finally, the remaining energies manufactured from the nodes were modernized. The suggested model has less PDR.

Pitchaimanickam and Murugaboopathi [31] have presented a hybrid firefly algorithm with PSO (HFAPSO) for optimal cluster head selection in wireless sensor networks. HFAPSO was presented for discovering the optimum CH selection in the LEACH-C approach. By using PSO, the presented hybrid algorithm enhances the overall search performance of fireflies. By using the presented method, the left over energy, count of alive nodes, throughput performance for the presented approach were assessed. But it did not give trust node computation.

Suresh Kumar and Vimala [32] have presented an EERP utilizing exponentially-Ant Lion Whale Optimization Approach (E-ALWO) in WSNs. The energy-efficient with trust-based routing approach was presented utilizing E-ALWO for routing the data packets to the receiver. Ideal and protected routes were used for transferring the data, and it was computed by the presented E-ALWO approach dependent on fitness measures. But it has a high delay.

3. Proposed Methodology

DDcGAN is optimized with hybrid Momentum search algorithm is proposed for securing data transmission through identifying the optimum CH at the network. Firstly, DDcGAN is considered to choose CH accurately. After selecting cluster head, a hybrid Momentum search algorithm with Giza Pyramids Construction algorithm hyb (MSA-GPCA) is proposed for better path selection. The block diagram of the proposed DDcGAN-MSA-GPCA-WSN-IoT method is depicted in Fig. 1.

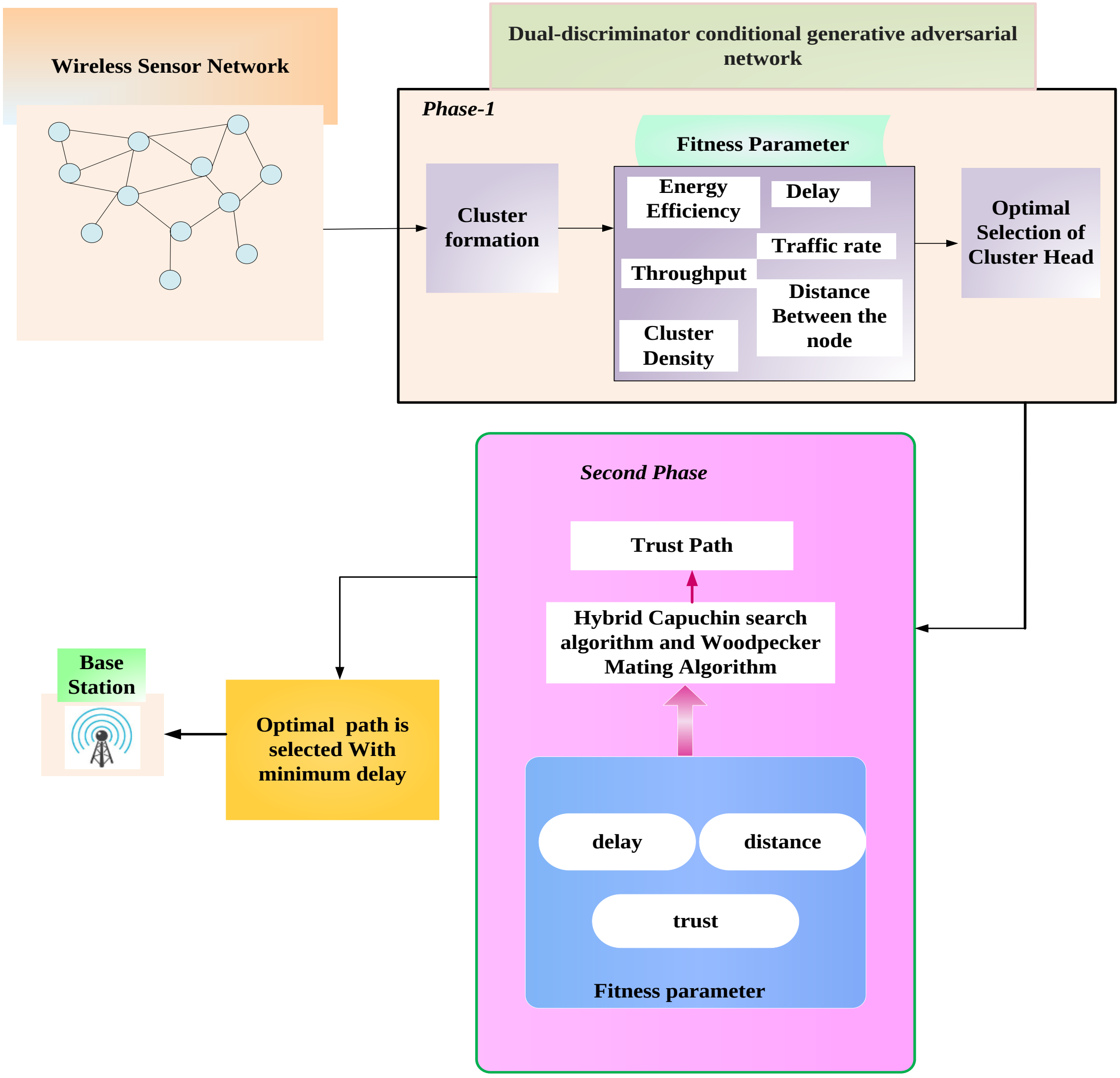

Fig.1. Proposed DDcGAN-MSA-GPCA-WSN-IoT method

3.1. *Network Model (Cluster Formation)*

A direct communication is carried out, and it is used between the sensor nodes within the radio range. To differentiate from the other sensors, each sensor node is placed with its distinctive personal ID. And within two ways, this procedure is carried out. Initially, CH is selected randomly, and the nodes of sensors are grouped together. Next, within the cluster, these nodes send their information to CH. Then, from all sensor nodes, the CH is used to collect information. To collect information at higher energy node, these CH nodes is selected. The Sensor nodes are location-aware. So, the cluster head selection is significant. For that reason, DDcGAN is proposed for CH selection; consequently, the energy efficacy of wireless sensor network is widespread.

Phase (1) CH selection

3.2. *Dual-discriminator Conditional Generative Adversarial Network (DDcGAN) for Cluster Head Selection*

Clustering is effective energy-conservation technique in WSN. A set of nodes forms the cluster. On every cluster, the CH has existed. The node connected to the head is regulated through the CH. So, the CH selection is significant. For that reason, DDcGAN is proposed for enhancing cluster head selection process.

A. Fitness Parameters

The process of clustering is recognized as there are many limitations of fitness. To choose better CH, the parameters, viz energy, delay, throughput, distance amid the node, traffic rate, cluster density is considered as actual CH selection. The fitness function is formulated in equation (1),

$$Fitness\left\{\left[1+\frac{Del(t)}{Del_{norm}}\right]+\left[1-\frac{Dis(t)}{X"*B*M}\right]+[En(t)]+[1-Traff(t)]+[1-den(t)]\right\}_{max} \tag{1}$$

here sensor nodes delay represents $Del(t)$ and Del_{norm}, $Dist(t)$ indicates distance among the sensor nodes and CH, $X" and B$ represents the total number of nodes in the cluster and amount of cluster head, the number of nodes in the network is denoted as M, $En(t)$ represents energy efficiency of cluster head, traffic rate, and cluster density is denoted as $Traff(t)\ and den(t)$. The mathematical formulation for each objective used in the proposed fitness parameter is briefly given as follows

Energy efficiency

The cluster head accomplishes three aspects; they are detecting, selecting, and collecting. CH takes maximal energy than other nodes. The fitness function is defined as vital that sharing equal energy with every network sensor. This is formulated in equation (2),

$$En(t)=\frac{1}{B}\sum_{j=1}^{B}En_{(t+1)}\,(H"_j) \tag{2}$$

where $En_{(t+1)}(H"_j)$ denotes cluster head updated energy that is formulated in equation (3)

$$En_{(t+1)}(H"_j)=En_t(H"_j)-En_{dissipation}(H"_j) \tag{3}$$

where $En_t(H"_j)$ is the cluster head energy at t a time, and $En_{dissipation}(H"_j)$ represents the cluster head dissipation energy.

Delay

The whole intermission taken by the node to transmit the packets is known as a delay. At the cluster, it lessens the count of nodes and then lessens the network latency. The delay depends on node Expected transmission count (ETC), propagated delay, and network communication, the delay is exhibited in equation (4),

$$Del(t)=\sum_{j=1}^{M}L_j^{"}(t)(\beta+\alpha_j) \tag{4}$$

where $L_j^{"}(t)$ represents the j^{th} Expected transmission count node at t time, β represents network transmission delay, and α_j represents the propagated delay of j^{th} node. ETC depends on the forwarded and received PDR of the node at t the time.

Throughput

It describes about the cluster head's growing data transmission to the BS. Throughput of CH is computed by eqn. (5),

$$Throughput=\sum_{i=1}^{n}CH_i\left[DT_{CH_i}(M_{CH_i},M_{BS})\right] \tag{5}$$

where DT_{CH_i} implicates CH’s data transmission speed, M_{CH_i} denotes CH location, M_{BS} refers BS location.

Distance among the nodes

This explains how wireless sensor networks need to take distance into account while transmitting information. When a cluster head is the only component of a sensor node, it determines how far apart the cluster's other members are measured from it. This is revealed in eqn (6) as follows,

$$Dis(t)=\frac{\sum_{k=1}^{n}\sum_{l=1}^{h}\ \|M_k^m-M_l^H\|+\|M_l^H-M^S\|}{\sum_{k=1}^{n}\sum_{l=1}^{h}\ \|M_k^m-M_l^H\|} \tag{6}$$

here n signifies entire count nodes, l signifies entire CHs count, M_k^m implies normal node, M_l^H implicates cluster head, M^S implicates sink node.

Traffic rate

This is minimal for effective network as well as traffic density on the basis of buffer utilization, packet drop, channel load network, traffic density computation with respect to an average of 3 parameters. Traffic density is revealed in eqn (7),

$$Traff(t) = \frac{1}{3}\left[B_{utilization} + P_{drop} + C_{Load}\right] \tag{7}$$

where, $B_{utilization}$ specifies buffer usage, P_{drop} represents packet drop, C_{Load} refers channel load.

Cluster density

The node signifies how to communicate in an ideal way. When density is high, it leads to maximize at congestion with packet drop. The density is defined as the ratio of the cluster's total nodes to the network's total nodes. This is expressed in eqn (8),

$$Den(t) = \frac{1}{M}\sum_{i=1}^{A}|Y_i| \tag{8}$$

Let $|Y_i|$ implies i^{th} cluster nodes, M implies overall nodes in network, and the entire count of CHs indicates A. Hence the CH is selected based on the above fitness parameter with the help of DDcGAN.

B. CH Selection Using DDcGAN

DDcGAN is employed for CH selection. DDcGAN is employed to choose the valuable nodes from the overall count of nodes in the network. DDcGAN allows the generator to be trained to fulfil severer necessities and avert the loss of information produced through the network. DDcGAN consists of two discriminators $D"_u \; and \; D"_j$ and a generator $G"$. The generator $G"$ consists of two de-convolutional layers and one encoder network, and the equivalent decoder network. The discriminator is intended to play a combative role beside the generator. Specially, $D"_u \; and \; D"_j$ separate the generated node from the number of nodes.

DDcGAN activates adversarial game betwixt the generator and 2 discriminators, which trains N a number of nodes that are mentioned as $DD = (1,2,3 \ldots N)$. The generator's goal is to make a real-like fused node depending on exactly calculated content loss to fault 2 discriminators when 2 discriminators differentiate the structure changes among the fused nodes and 2 source nodes for CH selection, respectively. In addition, DDcGAN is useful to determine the maximal energy efficiency of all nodes and minimize the traffic rate, cluster density, delay, and distance among the nodes. Based on the $G"$ training, the formula for minimizing and maximizing the objective function is expressed in below equation (9),

$$\begin{aligned}\min_{G"} \max_{D"_u, D"_i} & F[\log D"_v(u)] + F[\log(1 - D"_u(G"(u,j)))] \\ & + F[\log D"_j(j) + F[\log(1 - D"_j(\Im G"(u,j)))]\end{aligned} \tag{9}$$

where $\Im$ represents the down sample operator, $D"_u \; and \; D"_j$ represents the two adversarial discriminators, $G"(u,j)$ represents the generated node to be truthful and instructive enough to chump the discriminators.

In DDcGAN, the generator $G"$ train to chump the discriminators and limits the connection among the generated node and the source node. The generator loss process is collected via adversarial loss($loss_{G"}^{AD}$). Loss of content $loss_{cont}$ with ℓ weight can be formulated in equation (10),

$$loss_{G"} = loss_{G"}^{AD} + \ell loss_{cont} \tag{10}$$

From equation 10 $loss_{G"}^{AD}$ arises from the discriminator, and this can be formulated in equation (11),

$$loss_{G"}^{AD} = F[\log(1 - D_u^{"}(G"(u,j)))] + F[\log(1 - D"_j(\Im G"(u,j)))] \tag{11}$$

From equation (11), the content loss can be expressed in below (12)

$$loss_{cont} = F[\|\Im G"(u,j) - j\|_E^2 + \mu\|G"(u,j) - u\|_{TV"} \tag{12}$$

where, $TV"$ represents the TV norm to deal with the non-deterministic polynomial-time hard issue proficiently, μ represents the updated weight functions. From these updated weight functions, the network error is required to be low, consequently better solution is attained. DDcGAN presents effectual CH selection with minimum energy usage. After the CH selection, sensor nodes collect data's and fed to the cluster head. Cluster head receives the data then gives it to BS. Suppose there contains no authentication approach, malicious nodes will be received in the network, and it affects the whole network. So, a hybrid Momentum Search Algorithm (MSA) and Giza Pyramids Construction algorithm (GPCA) are proposed for optimal route path selection.

Phase 2 Optimal Path Selections

3.3. Optimal Path Selection Using Hybrid Momentum Search Algorithm (MSA) and Giza Pyramids Construction Algorithm (GPCA)

After the best CH selection, the multi-path communication is attained with the help of hyb MSA-GPCA algorithm. After CH selection, malicious nodes have arrived in the network, and it affects the whole network. Hence, 3 parameters are exhibited to select the optimum path from the network. An optimum route is carefully chosen for communicating the information from source to destination depending on three parameters such as trust, distance, and delay. The 3 parameters are labelled in eqn (13),

$$Fitness_{optimalpathx} = \left\{\left[1 + \frac{Del(t)}{Del_{norm}}\right] + \left[1 - \frac{Dis(t)}{X"*B*M}\right] + Trust(t)\right\} \quad (13)$$

Trust (Trust(t))

The trust is also called direct trust, which is depending on satisfaction among the node communications. The local trust among the node c in route $s"$ is depending upon transmitting, consistency, and packet loss rate factors. While node c satisfies the $s"$ route, the rate of satisfaction is higher, interpreting the direct trust. Then the trust $Trust(t)$ is expressed in equation (14)

$$Trust(t) = (1-\eta") \times RS_{c,s"}(h') \times FC_{c,s'}(h') \times LP_{c,s}(h') + \eta" \times Trust(t)(h'-1) \quad (14)$$

where, $RS_{c,s"}(h')$ represents the transmitting rate factor, $FC_{c,s'}(h')$ represents constancy factor, $LP_{c,s}(h')$ represents packet loss ratio factor, $\eta"$ represents continuous factor that is range between 0 to 1. The values of $Trust(t)$ are range between 0 and 1.

A. Hyb MSA-GPCA

Momentum Search Algorithm (MSA) is developed through Newton's laws that, mean conservation of momentum law. It contains a group of mass that deliberates the momentum conservation and solution bodies. At every iteration, an exterior body individually crashes by all solution bodies and moves in the direction of the optimal result. The crash direction is based on the solution body's location also the body location through the ideal fitness function. The optimum location is attained by permitting the exterior body to moves the solution bodies toward optimal locations. The updating location of all bodies of MSA is used to optimize the $Del(t)\ and\ Dis(t)$. Giza Pyramids Construction algorithm (GPCA) is based on the antique-inspired meta-heuristic algorithm. The GPCA is similar to Giza Necropolis, it is a place which consists of big three pyramids; all are constructed through the fourth dynasty of antique Egypt. GPCA is derived by the activities of the labors and pushing the stone slabs on the slope. Hence, the location of some labors substitute with others. This substitute changes the stone slab's movement and power balance. In the construction procedure, some labors are possibly to be a substitute and placed into a new location. The updating location of labors in GPCA is used to maximize the $Trust(t)$. The flow chart of hyb MSA-GPCA algorithm is implicated in Fig. 2. The stepwise procedure for hyb MSA-GPCA algorithm is explained below,

Step 1: Initialization

The population distribution of momentum search and the population of Giza Pyramids Construction is initialized uniformly in the solution space based on the below equation (15),

$$Y_j, g_k(t") = (y_j^c(t"),...y_j^m(t") + \eta_k nh\cos\theta) \quad (15)$$

where, $Y_{j,k}(t")$ represents the initial population of MSA with j^{th} position and body solution in $t"$ time and g_k is the kinetic resistance force of GPCA. Then $m and\ c$ represent the dimension of the MSA water bodies. Then n represents the stone slap masses, η_k represents the kinetic resistance coefficient, h represents the earth's gravity, θ represents the ramp angle of GPCA.

Step 2: Random Generation

After the process of initialization, GPCA and MSA input parameters are generated randomly. Here, appears maximal fitness values and then the selection of the better path is dependent on a fitness function.

Step 3: Compute the Fitness function

Create the random solution count from the initialized values. Fitness function is related to trust, delay, and distance among the node. The fitness function is calculated in equation (16).

$$Fitness_{optimalpathx} = \left\{\left[1 + \frac{Del(t)}{Del_{norm}}\right] + \left[1 - \frac{Dis(t)}{X"*B*M}\right] + Trust(t)\right\} \quad (16)$$

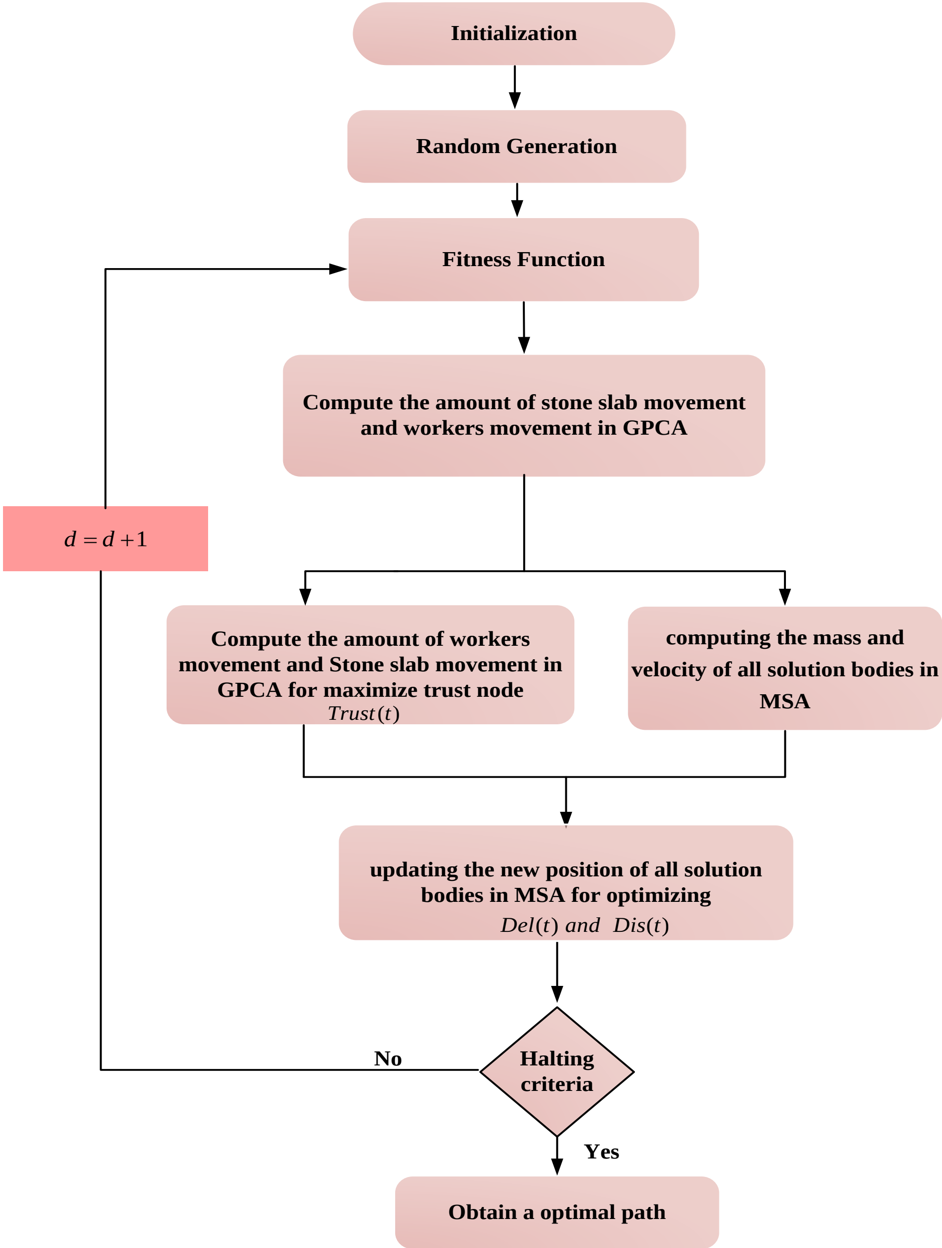

Fig.2. Flow chart of hyb MSA-GPCA algorithm

From equation 19 $Dis(t)$ represents the distance among nodes, $Del(t)$ represents the delay, $Trust(t)$ represent the trust. Fitness solutions must maximize trust, similarly minimizing the distance and delay. Hence, GPCA optimizes the $Trust(t)$, $Del(t)$ and $Dis(t)$ the parameter is optimized by MSA for optimal path selection.

Step4: Compute the amount of stone slab movement and workers movement in GPCA

The main point of GPCA is that labours push the stone slab continuously moved to increase the feasible control and feasible lead of the stone slab. These shock waves cause the employee to achieve non-repetitive displacement by pushing the stone slab well. Therefore, the stone movement on the slope can be calculated in equation (17),

$$Displacement\ of\ stoneslap = \frac{u_o^2}{2h(\sin\theta + \eta_k \cos\theta)} \quad (17)$$

where h represents the earth's gravity u_o represents the initial speed of the stone slab. The above expression is used to control the new position of the labors. Thus, the location of the labors pushes the stone slab is given in the below expression (18),

$$Movement\ of\ wor\ ker\ s = \frac{u_o^2}{2h\sin\theta} \tag{18}$$

where, θ represents the ramp angle

Step5: Position updating of stone slab movement (trust node with low power level) and worker displacement (best node selection) GPCA for optimizing $Trust(t)$

After computing the deviations of stone slab movement (trust path with low power level) and worker displacement (trust path selection) through the above equation (17 and 18), a new location can be attained from the subsequent of the above expressions. The new location can be attained by adding the stone slab movement of the exiting location that can be multiplied by the worker's movement. This updating location is a new resolution. Therefore, the updating position of the stone slab and the workers can be expressed in the below equation (19).

$$\vec{Q} = (\vec{Q}_i + c) \times y\vec{\sigma}_i \tag{19}$$

where, $\vec{Q}_i$ represents the current location, c represents the movement of the stone slab, y indicates the displacement of labour, $\vec{\sigma}_i$ represents the random vector that following the Uniform and Normal distribution. This worker movement is applied to examine the current best solution to attain the best global solution. This means the trusted node is achieved and eradicating the malicious node. This stone slab movement is used to choose a trusted node with lower power levels. From equation (18), the updated position will maximize the $Trust(t)$.

Step6: Computing the mass and velocity of all solution bodies in MSA

At each repetition, every solution body is stationary, and the separated exterior body is presented in the space called the exterior body. This body strikes with an additional body and alters its location towards the best one. Hence the mass and speed of external bodies decreased at the time, including the extreme mass of union for exterior bodies. The speed and mass of exterior bodies are computed in the below equations (20 and 21),

$$N(t") = 1 - \frac{t"-1}{T"-1} \tag{20}$$

$$V^{(c)}{}_j(t") = s_1.(1 - \frac{t"-1}{T"-1}).V \quad {}^{c}_{best}{}^{c}_{j}{}_{max} \tag{21}$$

where $N(t")$ indicates mass solution body with time $t"$, $T"$ implies maximum count of iterations. Then $V^{(c)}{}_j\ (t")$ represents the speed of the exterior body with c dimension, and j^{th} system body iteration s_1 represents the random term, V_{max} represents the reality of the random number, $y^c_{best}(t")\ and\ y^c_j(t")$ and represents the values of system body c dimensions along finest fitness for j^{th} system body iteration.

Step7: Updating the new position of all solution bodies in MSA for optimizing $Del(t)\ and\ Dis(t)$

After collisions, the new position is achieved with the help of speed equations (20 and 21), It shows that the present location of everybody is the summary of a ratio of its preceding location and a ratio of its speed after collision. Then the new position of the body can be given in equation (21),

$$y^c_j(t"+1) = y^{(c)}_j(t") + s_2 U^c_j(t") \tag{22}$$

The above equation $U^c_j(t")$ denotes updating position of system speed with c dimension and j^{th} system body iteration at $t"$ and s_2 is the random term by an unchanged distribution within the [0, 1] range. From equation (18), the updated position will minimize the $Del(t)\ and\ Dis(t)$.

Step8: Termination

Stop the process after obtaining the best solution in equations (16) to (22) is repeated until the conditions are met. At last, equations (17) to (22) will provide the optimal path with minimum distance and minimum delay. The output of the hyb - MSA-GPC algorithm provides an optimal path, which iteratively repeats step 3 until halting criteria $d = d + 1$ is met. The ideal trust path transfers the data to BS.

4. Result with Discussion

The segment describes the performance of dual-discriminator conditional generative adversarial network optimized with hybrid Momentum search algorithm and Giza Pyramids Construction algorithm for Cluster-based Routing in WSN-assisted IoT. The proposed technique is carried out in NS2 along 2 GB RAM, Intel core processor, Windows 10 OS. To evaluate how well the suggested strategy works, the performance measures are broken down and analyzed. The performance is analyzed with existing DBN-MRFO-CBR-WSN-IoT, GWO-CBR-WSN-IoT, BWO-CBR-WSN-IoT, and PSO-CBR-WSN-IoT methods. Table 1 displays the parameters utilized in the simulation.

Table 1. Parameters utilized in the simulation

Simulation parameters	**Values**
Replication area	$(1000 \times 1000) sqm$
Nodes count	50
Nodes energy	$0.5J_1$
Packages count to be sent	$250 bytes_1$
Simulation time	$4600 sec$
Locality of BS	400,600
Network	Wireless sensor
Number of rounds	200

4.1. Performance Metrics

This is employed to determine the results and is deliberated below,

A. Network Lifetime

It implies how many time/rounds the network activating this function. This is computed by eqn (23),

$$Networklifetime = min_j \left[\frac{\sum_{i=1} CM_{ij} * LS_i}{NN_j}\right] \tag{23}$$

where, CM_{ij} refers coverage matrix, LS_i implies life of the sensor node, M_j implies number of nodes

B. Number of Alive Nodes

It delineates the sensor node by getting sufficient energy to execute the task. This is computed by eqn (24),

$$M_X^i = Re^i(m) > 0 \tag{24}$$

From eqn (23), $Re\, s^i\,(m)$ refers residual energy node on i^{th} round.

C. Packet Delivery Ratio

The data packets ratio distributed proficiently to the base station including count of nodes. This is scaled by eqn (25),

$$PDR = \frac{\sum No.of packets received}{\sum No.of packets send} \times 100\% \tag{25}$$

D. Delay

It represents the time it takes to deliver the packets from transmitter to receiver. It is measured by seconds. This is computed by eqn (26),

$$delay = T_S - T_R \tag{26}$$

here T_S denotes sending period of message, T_R denotes receiving period of message.

E. Drop

This is nothing but packet loss rate and is computed by eqn (27)

$$Packetdrop = \frac{Totalpacket - Tota\ln umber of received packet}{TotalNumber of packet} \tag{27}$$

F. Energy Efficiency

The Energy Efficiency formula can be calculated in eqn (28),

$$EE = \xi_{tr} + \xi_{re} \tag{28}$$

where, ξ_{tr} represents the transmitted energy, and ξ_{re} represents the received energy.

4.2. Performance Comparison of Various Models

Fig. 3 to 9 depicts the performance metrics. The results acquired through performance metrics are analyzed to the existing DBN-MRFO-CBR-WSN-IoT, GWO-CBR-WSN-IoT, BWO-CBR-WSN-IoT, and PSO-CBR-WSN-IoT methods.

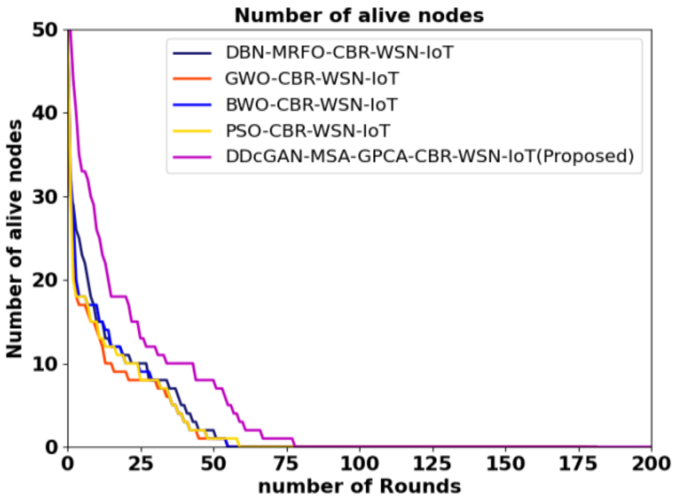

Fig.3. Performances of alive node analysis

Fig. 3 implicates rounds Vs alive nodes analysis. Here, the proposed DDcGAN-MSA-GPCA-CBR-WSN-IoT method attains 50%, 87.5%, 50% and 50% higher alive node for round 25; 75%, 87.5%, 87.5% and 87.5% higher alive node for round 50 compared with existing methods, like DBN-MRFO-CBR-WSN-IoT, GWO-CBR-WSN-IoT, BWO-CBR-WSN-IoT and PSO-CBR-WSN-IoT respectively. Table 2 depicts Performances of alive node Analysis.

Table 2. Performances of alive node Analysis

Rounds	25	50	75	100	125	150	175	200
DBN-MRFO-CBR-WSN-IoT	10	2	0	0	0	0	0	0
GWO-CBR-WSN-IoT	8	1	0	0	0	0	0	0
BWO-CBR-WSN-IoT	10	1	0	0	0	0	0	0
PSO-CBR-WSN-IoT	10	1	0	0	0	0	0	0
DDcGAN-MSA-GPCA-CBR-WSN-IoT (Proposed)	15	8	1	0	0	0	0	0

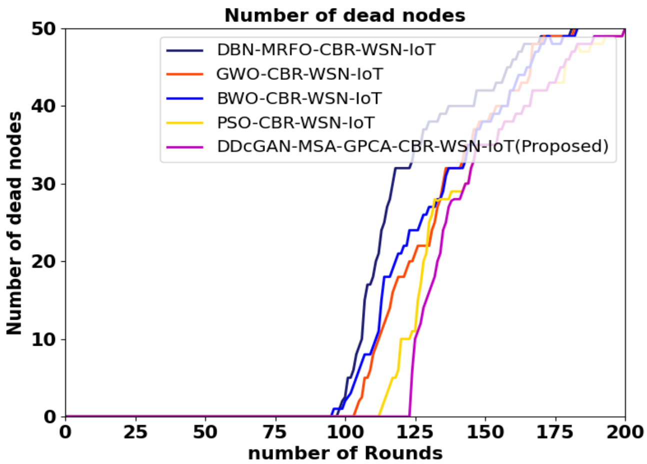

Fig.4. Performances of dead nodes analysis

Fig. 4 represents round Vs dead nodes analysis. Here, the proposed DDcGAN-MSA-GPCA-CBR-WSN-IoT method attains 45.94%, 10%, 30% and 42% lower dead node for round 150; 20%, 11% and 11% lower dead node for round 175; 13%, 13%, 11% and 4% lower dead node for round 200 compared with existing methods, like DBN-MRFO-

CBR-WSN-IoT, GWO-CBR-WSN-IoT, BWO-CBR-WSN-IoTand PSO-CBR-WSN-IoT respectively. Table 3 depicts Performances of dead nodes Analysis.

Table 3. Performances of dead nodes analysis

Rounds	25	50	75	100	125	150	175	200
DBN-MRFO-CBR-WSN-IoT	0	0	0	0	6	37	42	49
GWO-CBR-WSN-IoT	0	0	0	0	0	22	39	49
BWO-CBR-WSN-IoT	0	0	0	0	4	26	39	48
PSO-CBR-WSN-IoT	0	0	0	0	0	14	35	45
DDcGAN-MSA-GPCA-CBR-WSN-IoT (Proposed)	0	0	0	0	0	20	35	43

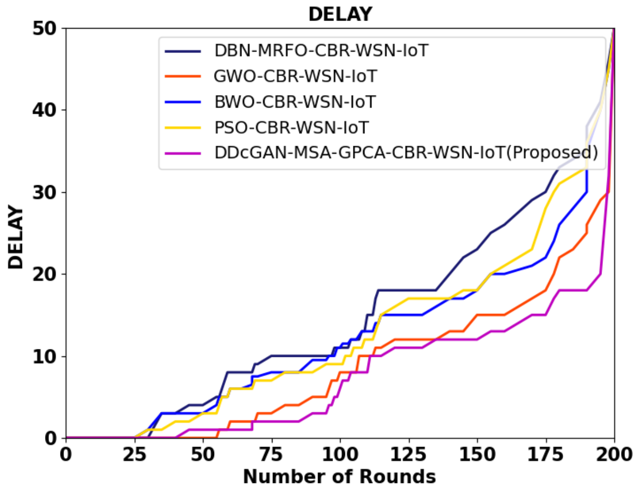

Fig.5. Performances of delay analysis

Table 4. Performances of delay analysis

Rounds	25	50	75	100	125	150	175	200
DBN-MRFO-CBR-WSN-IoT	0	0	5	13	20	21	33	50
GWO-CBR-WSN-IoT	0	0	2	14	16	17	29	51
BWO-CBR-WSN-IoT	0	3	4	11	14	15	27	52
PSO-CBR-WSN-IoT	0	2	3	12	13	13	24	50
DDcGAN-MSA-GPCA-CBR-WSN-IoT (Proposed)	0	1	2	8	12	12.5	19	47

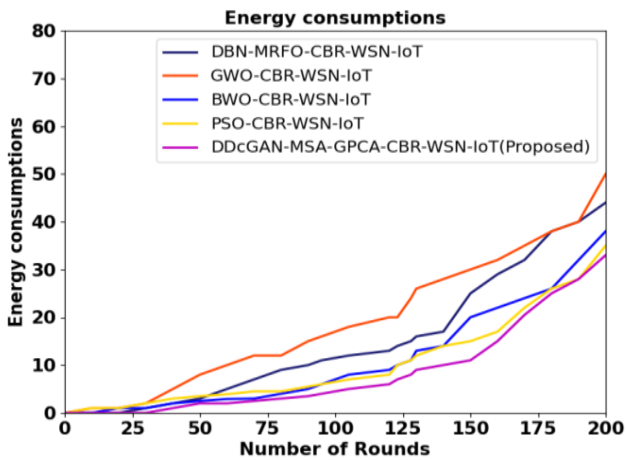

Fig.6. Performances of Energy consumption analysis

Fig. 5 depicts rounds Vs delay analysis. Here, the proposed DDcGAN-MSA-GPCA-CBR-WSN-IoT method attains 62%, 75%, 37% and 50% lower delay for round 100; 66%, 33%, 16% and 8% lower delay for round 125; 68%, 36%, 20% and 4% lower delay for round 150; 73%, 52%, 42% and 26% lower delay for round 175; 6%, 8%, 10% and

6% lower delay for round 200 compared with existing methods, like DBN-MRFO-CBR-WSN-IoT, GWO-CBR-WSN-IoT, BWO-CBR-WSN-IoT and PSO-CBR-WSN-IoT respectively. Table 4 depicts Performances of delay Analysis.

Fig. 6 portrays rounds Vs energy consumption analysis. Here, the proposed DDcGAN-MSA-GPCA-CBR-WSN-IoT method attains 20%, 79%, 0.64% and 44% lower Energy consumption for round 50; 33%, 75%, 66% and 50% lower Energy consumption for round 75; 60%, 0.7%, 58% and 40% lesser energy consume for round 100; 42%, 65%, 50% and 42% lesser energy consume for round 125; 40%, 64%, 70% and 40% lesser energy consume for round 150; 17%, 70%, 56% and 7% lesser energy consume for round 175; 14%, 42%, 42% and 10% lesser energy consume for round 200 when comparing to the existing methods, like DBN-MRFO-CBR-WSN-IoT, GWO-CBR-WSN-IoT, BWO-CBR-WSN-IoT and PSO-CBR-WSN-IoT respectively. Table 5 depicts Performances of Energy consumption analysis.

Table 5. Performances of energy consumption analysis

Rounds	25	50	75	100	125	150	175	200
DBN-MRFO-CBR-WSN-IoT	1	3	4	8	10	14	24	32
GWO-CBR-WSN-IoT	2	12	12	18	20	28	35	40
BWO-CBR-WSN-IoT	1	7	9	12	14	17	32	40
PSO-CBR-WSN-IoT	2	4.5	4.5	7	10	14	22	28
DDcGAN-MSA-GPCA-CBR-WSN-IoT (Proposed)	0	2.5	3	5	7	10	20.5	28

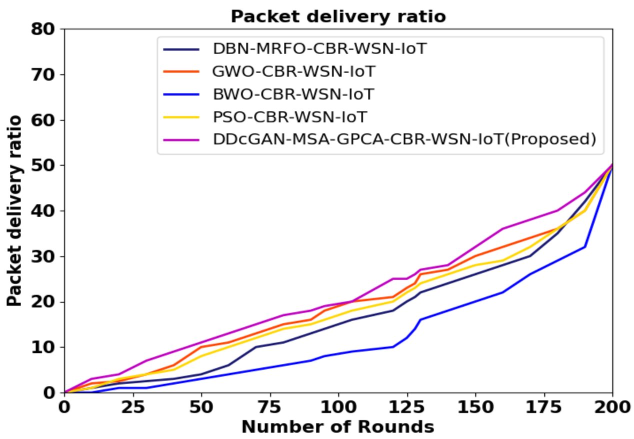

Fig.7. Performances of packet delivery ratio analysis

Fig. 7 illustrates rounds Vs packet delivery ratio analysis. Here the proposed DDcGAN-MSA-GPCA-CBR-WSN-IoT method attains 85%, 75%, 64% and 75% better PDR for round 25: 25%, 18%, 53% and 30% better PDR for round 50; 61%, 12.5%, 38% and 20% better PDR for round 75; 55%, 0.02%, 25% and 11% better PDR for round 100; 85%, 8%, 23%, 13% better PDR for round 125; 60%, 6%, 23% and 14% better PDR for round150; 63%, 12.5%, 28%, 24% better PDR for round 175; 46%, 11%, 26% and 18% better PDR for round 200 comparing to the existing methods, like DBN-MRFO-CBR-WSN-IoT, GWO-CBR-WSN-IoT, BWO-CBR-WSN-IoT and PSO-CBR-WSN-IoT respectively. Table 6 depicts Performances of Packet delivery ratio analysis.

Table 6. Performances of packet delivery ratio analysis

Rounds	25	50	75	100	125	150	175	200
DBN-MRFO-CBR-WSN-IoT	1	4	7	9	14	20	22	26
GWO-CBR-WSN-IoT	4	11	16	20	24	30	32	34
BWO-CBR-WSN-IoT	2.5	6	13	16	21	26	28	30
PSO-CBR-WSN-IoT	4	10	15	18	23	28	29	32
DDcGAN-MSA-GPCA-CBR-WSN-IoT (Proposed)	7	13	18	20	26	32	36	38

Fig. 8 depicts rounds Vs network lifetime analysis. Here, the proposed DDcGAN-MSA-GPCA-CBR-WSN-IoT method attains 4.55%, 6.09%, 2.46% and 4.69% better network lifespan for round 25; 9.63%, 12.55% 6.05%, 7.92% better network lifespan for round 50; 20.42%, 18.27%, 12.64%, 13.51% better network lifespan for round 75; 30.45%, 29.99%, 23.77% and 19.39% better network lifespan for round 100; 40.58%, 52.96%, 39.54%, 27.89% better network lifespan for round 125: 70.58%, 67.84%, 52.06% and 30.90% better network lifespan for round 150; 51.59%, 51.75%, 70.98% and 41.58% better network lifespan for round 175; 58.37%, 66.94%, 49.23% and 63.49% better network lifespan for round 200 comparing with existing methods, likes DBN-MRFO-CBR-WSN-IoT, GWO-CBR-WSN-IoT, BWO-CBR-WSN-IoT and PSO-CBR-WSN-IoT respectively. Table 7 depicts Performances of Network life time Analysis.

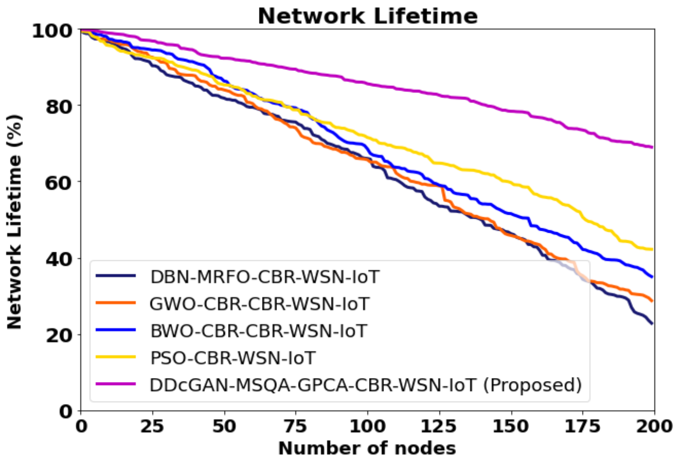

Fig.8. Performances of network lifetime analysis

Table 7. Performances of network life time analysis

Rounds	25	50	75	100	125	150	175	200
DBN-MRFO-CBR-WSN-IoT	92.73	84.21	74.27	65.83	58.94	45.99	35.65	28.71
GWO-CBR-WSN-IoT	91.38	82.02	75.62	66.07	54.17	46.74	35.51	22.80
BWO-CBR-WSN-IoT	94.62	87.05	79.40	69.39	59.38	51.59	43.05	35.02
PSO-CBR-WSN-IoT	92.60	85.54	78.79	71.94	64.79	59.93	51.99	42.19
DDcGAN-MSA-GPCA-CBR-WSN-IoT (Proposed)	96.95	92.32	89.44	85.89	82.86	78.45	73.61	68.98

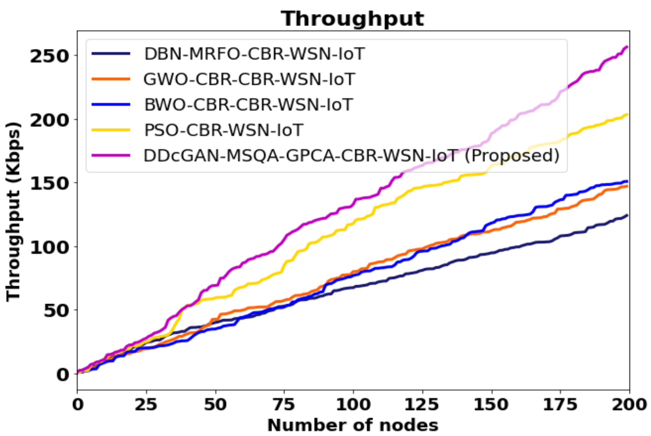

Fig.9. Performances of throughput analysis

Table 8. Performances of throughput analysis

Rounds	25	50	75	100	125	150	175	200
DBN-MRFO-CBR-WSN-IoT	22.57	39.10	52.31	67.07	80.2	93.8	106.2	123.8
GWO-CBR-WSN-IoT	18.98	42.21	56.41	77.3	97.4	111	128.9	146.8
BWO-CBR-WSN-IoT	19.79	34.60	51.43	75.5	95.6	116.96	135.2	150.6
PSO-CBR-WSN-IoT	23.84	58.33	79.41	116.7	145.6	160.26	181.2	203.1
DDcGAN-MSA-GPCA-CBR-WSN-IoT (Proposed)	26.45	68.73	101.9	130.6	162.5	183.2	216.7	256.2

Fig. 9 illustrates rounds Vs throughput analysis. Here, the proposed DDcGAN-MSA-GPCA-CBR-WSN-IoT method attains 17.19%, 39.35%, 33.65% and 10.94% higher throughput for round 25; 75.78%, 62.82%, 98.64%, 17.82% better throughput for round 50; 94.80%, 80.64%, 98.13%, 28.32% better throughput for round 75; 94.72%, 68.95%, 72.98% and 11.91% higher throughput for round 100; 50.64%, 66.83%, 69,97% and 11.60% higher throughput for round 125: 95.30%, 65.04%, 56.63% and 14.31% higher throughput for round 150; 50.99%, 68.11% 60.28% and

19.59% higher throughput for round 175; 51.67%, 74.52% 70.11%, 26.14% better throughput for round 200 compared with existing methods, likes DBN-MRFO-CBR-WSN-IoT, GWO-CBR-WSN-IoT, BWO-CBR-WSN-IoT and PSO-CBR-WSN-IoT respectively. Table 8 depicts Performances of throughput Analysis.

4.3. *Justification of Study*

In this study explored the use of a dual-discriminator conditional generative adversarial network optimized with a hybrid Momentum search algorithm and Giza Pyramids Construction algorithm for Cluster-Base Routing at WSN Assisted IoT for securing data transmission by identifying the optimal cluster heads. The results demonstrated that our deep learning model could select the optimal CH, obtain the state-of-the-art results and have good generalization. In addition, a likely increase in performance by optimal trust path selection using hyb MSA-GPCA approaches.Simulation results illustrate that the Proposed DDcGAN-MSA-GPCA-WSN-IoT methodprovide higher packet delivery ratio of 38.58%, 25.69%, 12.76% and 43.87%, minimum delay of 23.64%, 54.39%, 15.76% and 31.91%, lower energy consumption of 32.67%, 45.17%, 10.09% and 45.39%; 58.31%, 12.39%, 34.98% and 56.34% higher network lifetime compared with existing methods like DBN-MRFO-CBR-WSN-IoT, GWO-CBR-WSN-IoT, BWO-CBR-WSN-IoT and PSO-CBR-WSN-IoT respectively.

5. Conclusions

In this manuscript, a dual-discriminator conditional generative adversarial network optimized with hybrid Momentum search algorithm and Giza Pyramids Construction algorithm for Cluster base Routing in WSN Assisted IoTs (DDcGAN-MSA-GPCA-CBR-WSN-IoT) is implemented successfully for securing data transmission through recognizing the optimum CHs in wireless sensor network. The simulation is done on the NS2 platform. The proposed DDcGAN-MSA-GPCA-CBR-WSN-IoT method attains High throughput 17.83%, 98.60%, 62.84%, and 75.79% and lower energy consumption of 44.44%, 64.28%, 79.16%, and 16.66% compared with the existing methods, like DBN-MRFO-CBR-WSN-IoT, GWO-CBR-WSN-IoT, BWO-CBR-WSN-IoT, and PSO-CBR-WSN-IoT respectively.

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Authors' Profiles

Darshan B. D. received his BE degree in Electronics & Communication Engineering from Visvesvaraya Technological University, Belgaum in 2008 and his MTech degree in Digital Electronics & Communication System from Visvesvaraya Technological University, Belgaum, India in 2011. He is currently working as the Assistant Professor at the Department of Electronics and Communication Engineering, S J B Institute of Technology, Kengeri, Bengaluru-560060, Karnataka, India. His research interests include computer networking, communication engineering, and wireless sensor networks.

Prashanth C. R. received his BE degree in electronics, ME degree in digital communication, and the PhD degree from Bangalore University, Bangalore, India. He is currently working at the Department of Electronics & Telecommunication Engineering and is Professor and Dean (Examinations) at Dr. Ambedkar Institute of Technology, Bengaluru-560056, Karnataka, India. His areas of interest are image processing, pattern recognition, biometrics, computer networks, communication engineering, device modelling. and engineering education. He has over 50 research publications in refereed International Journals and Conference Proceedings.

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