

Hybrid GOA and GA Algorithm based Deep Belief Network for Network Controlled Vertical Handoff

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Abstract: The inventive character of diverse heterogeneous wireless networks presents improved service. The different WAN comprise wireless Metropolitan Access Network (WMANs), as well as cellular networks. For the selection of dynamic networks, several models are formulated however these models are determined on obtaining the enhanced performance. A new technique is formulated to enhance the energy effectuality of disparate heterogeneous wireless networks to the addressed aforesaid problem. Moreover, the adopted Hybrid Grasshopper Optimization Algorithm (GOA) and Genetic Algorithm (GA) is exploited in this paper. Moreover, the fitness model is taken into consideration with certain metrics which comprises Average bit rate (ABR), Delay, jitter, Bit Error Rate (BER), packet loss, energy utilization, hotspot probability, as well as Received signal strength (RSS). The adopted Hybrid GOA-GA Optimization approach is exploited to train DBN to choose optimal weights. Moreover, the selection of network metrics is subjected as input to adopted Hybrid GOA) and GA based Deep Belief Network (DBN), whereas the optimal decision is made to hold vertical handoff. The adopted Hybrid GOA-GA based DBN presented enhanced performance with minimum probability of call drop, delay, energy utilization, and maximum throughput.

Keywords: Delay, Energy, Heterogeneous Network, Vertical handoff, Wireless network, WMANs.

Nomenclature

Abbreviations	Descriptions
GOA	Grasshopper Optimization Algorithm
BER	Bit Error Rate
MS	Mobile Station
GPS	Global Positioning System
DBN	Deep Belief Network
ACO	Ant Colony Optimization
WAN	Wireless Access Networks
GA	Genetic Algorithm
RSS	Received Signal Strength
ANN	Artificial Neural Network
ABC	Artificial Bee Colony
WSN	Wireless Sensor Networks
ABC	Always Best Connection
IoT	Internet of Things
SA	Simulated Annealing
QoE	Quality of Experience
PSO	Particle Swarm Optimization
MADM	Multiple Attribute Decision Making
DE	Differential Evolution
WiMAX	Worldwide Interoperability For Microwave Access
QoS	Quality of Service
FAHP	Fuzzy Analytic Hierarchy Process
BPNN	Back Propagation Neural Network
VHDC	Vertical Handoff Decision Controllers
APs	Access Point
LSN	Large scale network

SNR	Signal to Noise Ratio
TAP	Target Access Point
ATM	Asynchronous Transfer Network
PRSS	Predictive Received Signal Strength
WLAN	Wireless Local Area Network
PoA	Point of Attachment
UMTS	Universal Mobile Telecommunications System
CR	Cognitive Radio
MSN	Medium scale network
TOPSIS	Technique for Order Preference by Similarity to an Ideal Solution

1. Introduction

The wireless technologies development is the result of exponential increases as well as extensive extends mobile devices deployment, services as well as applications [1]. To present seamless communication as well as ubiquitous and at a worldwide level, it is necessary to extend a model in that a user can progress in a heterogeneous environment with enduring communication availing obligatory QoS. In a heterogeneous environment, choosing the optimal wireless network is an important problem to understand ubiquitous connectivity. Currently, 2G, as well as 3G networks, coincide to achieve supplies of service as well as diverse coverage targets. In the ongoing service, the user prefers to hold both the network uninterrupted, so the optimal network selection is required. MS is exploited for the network selection initialization or it can be on the basis of the link quality measurements by the network. For network selection, the RSS is considered as the extensively exploited parameter. Basically, it is observed that severe ping-pong affects outcomes from the chosen on the basis of the RSS thresholds. Long handoff delay, minimum network throughput, and maximum dropping probability are effects of the ping-pong effect. For the selection of networks, the probability of outage is considered as one of the main parameters in multimedia applications. It is ascertained on the basis of the least acceptable signal strength or receiver sensitivity. It is stated as probability while the immediate RSS falls under a particular threshold. The MS position information is presented using the GPS, which is enthused in creating a selection of network decisions as well as link parameter measurements [2].

Ever since 4G communication standards were subjected, therefore in the worldwide, numerous research institutions were investigating the subsequent generation of 5G communication standards as well as appropriate technology. For the balance between suppliers, operators, as well as users, several heterogeneous wireless networks will coincide as well as a complement for an extensive period. Therefore, the development of heterogeneous network combinations is rapidly developed that is obviously special with the introduction of IoT. How to choose a TAP to make sure proficient communication between two terminals or nodes in the system has to turn out to be an essential obligation for numerous practical application cases, for instance, Social Internet of Vehicles, Scale-Free WSN [10]. For users, to attain a maximum QoE to be ABC, the mobile terminal requires to switch among diverse networks. Vertical handover represents the switching behavior. To end network operators as well as users, essential vertical handovers can carry profit, while superfluous vertical handovers can humiliate user QoE and general the performance of the network. Therefore, it has turned out to be attractive as well as challenging research subject to select an optimal one from numerous candidate networks [3].

On basis of MADDM, it must be stated that as well as to these methods, numerous meta-heuristic approaches were used for this problem, namely GA, SA, ANN, Q-Learning, PSO, ACO, GASA. Nevertheless, all these known as intelligent approaches should be iterated numerous times using probabilistic rules, as well as subsequent to the best outcomes are slowly attained. Generally, unwanted or even awful outcomes are produced without adequate iteration. Therefore, sufficient iterations are needed before the preferred outcomes are attained. Or else, any intelligence of approaches will not be replicated. As it is known, the vertical handoff decision time procedure must be briefly as probable from the perspectives of both the network operator as well as end-user. Therefore, it restricts these approaches' application in the network selection context [5].

The main contribution of this paper is to formulate an important model for network-controlled vertical handoff in different, heterogeneous WSN taking into consideration of mobility problem therefore mobile terminals have the ability to travel in several access networks. The adopted model carries out vertical handoff management on the basis of effectual selection of network model. Initially, sensor nodes confirm the requirement of data rate and if the rate is less a definite threshold, it starts handover. Subsequently, an optimization approach, called Hybrid GOA-GA is adopted for the effectual network selection. In addition, the fitness model is newly formulated by exploiting the definite metrics that comprise jitter, BER, packet loss, delay, ABR energy utilization, hotspot probability, as well as RSS. To train DBN the adopted Hybrid GOA-GA is used to choose the optimal weights. Moreover, the selection of network metrics is taken into consideration as an input to DBN in which an optimal decision is performed to hold

the vertical handoff. Hence, the adopted important models administer the vertical handoff in the different, heterogeneous networks by exploiting the adopted Hybrid GOA-GA -based DBN model.

2. Literature Review

In 2018, He-Wei Yu and Biao Zhang [1], worked on a heterogeneous network chosen approach on the basis of the integration of user preference as well as the attribute of the network. For each candidate network in full awareness of user preferences and actual circumstances of heterogeneous networks, the approach integrates three characteristic MADM techniques, called Entropy, FAHP, and TOPSIS. Initially, FAHP was exploited to compute the biased network attributes weights and biased helpfulness values of all substitutes for four characteristic traffic classes, and subsequently exploit TOPSIS and Entropy to correspondingly acquire the network attributes objective weights as well objective usefulness values of all alternatives. At last, as stated by the complete usefulness value of each candidate network as well as a threshold, the majority suitable network, whose complete utility value was utmost as well as more than equivalent value of a current network of the mobile terminal, was chosen to access. In 2005, S. Balasubramaniam and J. Indulska [2], proposed a vertical handover model appropriate for multimedia applications in enveloping systems. This work focused on the handover decision-making procedure that uses context information concerning user devices, network environment user position, as well as requested QoS. In 2015, Kiran Ahuja et al [3] developed a technique for network selection on the basis of the outage probability averaged RSS, as well as distance and the developed model consists of two phases. In the initial phase, suppose that network conditions were leading in the selection of network, the overlapping region was recognized via estimation of distance. In a subsequent phase, the selection of network approach on basis of averaged RSS and outage was appealed to choose the optimum network. In 2017, Krishan Kumar et al [4], motivated the expansion of a spectrum handoff model with MADM techniques like easy preservative weighting, a model for order inclination by the resemblance to the perfect solution, a grey relational analysis as well as a cost function based technique. The preferences of CR were on the basis of video, voice, as well as data services, named triple-play services. In 2020, Sunisa Kunarak et al [5], worked on a multi-criteria vertical handoff decision approach and dwell time to attain an acceptable QoS by exploiting the optimal selection of access network in a combined WLAN, a WiMAX, and a UMTS. Handoffs were categorized into two classifications such as WLAN/WiMAX originating handoff as well as UMTS originating handoff (downward). For real-time and non-real-time services initial criteria were developed. The measures which were needed to activate a handoff were the neighbor networks PRSS as well as RSS attained from the present network. For the prediction, the BPNN was learned.

3. System Model

For vertical handoff, the system model of different and heterogeneous wireless networks is described. Here, WLAN is configured by taking into consideration of the minute cells with cellular coverage area. Suppose consider A as APs group in the cellular coverage area, as well as it is indicated as $A = \{a_1, a_2, \dots, a_N\}$. Presume Bindicate BS possessing cell coverage area and devised as $B = \{b_1, b_2, \dots, b_M\}$. It is seen that, $M=1$ exclusive of the scenario of enormous opaque urban deployment. Suppose $M > 1$, then APs are placed in the cellular coverage area. Hence, A as well as B is handled by VHDC with cellular coverage areas.

It is exploited to put available APs into the set A, as well as data are collected from load status taking into consideration every AP from the set A as well as every Base Station from the set B. Therefore, it is exploited to augment the available APs into a set A, as well as data are accrued from the load status taking into consideration every AP from the set A and every BS at the set B. The group of all mobile nodes is devised as $\bar{P} = \{p_1, p_2, \dots, p_K\}$ from the cellular coverage area. Therefore; using mobile initiates the handoff by taking into consideration of mobile node; in which each mobile node either requests handoff or service by AP which belonged to A or BS that be owned by B without mobility. Therefore, the collection of every MN is divided into subsets at a definite time interval which is stated as follows:

$$P_m = \{p_{n1}, p_{n2}, \dots, p_{n_{q(m)}}\} \quad (1)$$

Wherein, the $q(m)$ indicates the total count of mobile nodes which request handoff at the time m , as well as $n_1, n_2, \dots, n_{q(m)}$ indicates MNs indexes, as well as $T_m = \bar{P} - P_m$.

3.1. Primary Model of Heterogeneous Network

a) *Heterogeneous devices:*

The devices which are linked to the heterogeneous network have various configurations. For instance, battery constraints computational abilities, device mobility pattern, and network interface management.

b) *Radius model for communication:*

T represents the communication model of the device as well as device coverage range with radius s is centered at C from another device.

$$G(c,s) = \{H_1, H_2 \in N : |\delta(H_1 - H_2)| \leq \alpha_{H1}\} \quad (2)$$

wherein, M implies organized AP as well as BS, and distance amid 2 APs or BSs from the heterogeneous network is stated as $\delta(H_1 - H_2)$, G implies coverage distance.

c) *MSN*

If the wireless network is modified in a closed area as well as handover is performed with diverse MNs, subsequently, all nodes carried out regular handovers for medium scale network in MSN. Suppose that, 100 nodes are deployed with 500m×500m area as MSN in the closed region. Subsequently, the explanation is devised as $\forall h \ell \wedge \ell \in N, |\delta(\ell - AP/BS)| < \alpha_\ell$, wherein, ℓ implies MN, and distance amid BS as well as MN is stated as $\ell - AP/BS$.

d) *LSN*

If total hops among MN as well as end node is maximum in LSN, subsequently network is taken into consideration as LSN and is devised as $\exists \ell \wedge \ell \in N, |\delta(\ell - AP/BS)| > \alpha_\ell$, wherein, BS or AP from the set N is indicated as ℓ , as well as $\ell - AP/BS$ represents distance computation among AP or BS as well as MN in which end node is linked.

e) *Mobility model*

In this section, the mobility approach [6] of the heterogeneous network is explained. Additionally, each macro-cell area poses diverse hotspots with WLAN coverage. Besides, the hotspot size is in the single WLAN AP range as well as micro-cell coverage. The radius hexagon cell R as well as r represents macro-micro-cell for analysis. Two types of user mobility are deployed, one is vehicular as well as other is varied non-vehicular as well as vehicular in macro-cell.

Let T_{M_WWAN} indicate arbitrary variables having macro-cell residence times with pdf $f_{mWWAN}(t)$. Therefore, vehicular mobility user hotspot residence time is a random variable, T_{MWWAN} , that is devised as follows:

$$T_{mWWAN} = \left(\frac{r_{eff}}{R_{eff}} \right) T_{MWWAN} = \frac{r}{R} T_{MWWAN} \quad (3)$$

wherein, R_{eff} indicate hotspot area radius as well as r_{eff} indicate macro cell radius.

In the hotspot area, the vehicular users stated as below:

$$f_{mWWAN}(t) = \left(\frac{1}{c} \right) f_{MWWAN} \left(\frac{t}{c} \right) \quad (4)$$

wherein, $c = \frac{r}{R}$.

4. Adopted Vertical Handoff Model

Fig 1 demonstrates the vertical handoff management by exploiting the adopted Hybrid GOA-GA based DBN to deliver MN with a suitable handover triggering point as well as optimized chosen the network. Initially, sensor nodes examine the required rate of data as well as if the data rate is lesser than the pre-defined threshold, subsequently, the handover is started. Subsequently, numerous metrics such as “packet loss, EED, BER, Jitter, energy, RSS Probability of the out-of-hotspot user moving into a hotspot, and ABR parameter”. Additionally, the optimization model, called Hybrid GOA-GA is formulated. Moreover, the adopted Hybrid GOA-GA is exploited to select the optimal handover decision as well as an optimal network is performed by exploiting DBN using a fitness model. To handle the vertical handoff the optimal decision is performed.

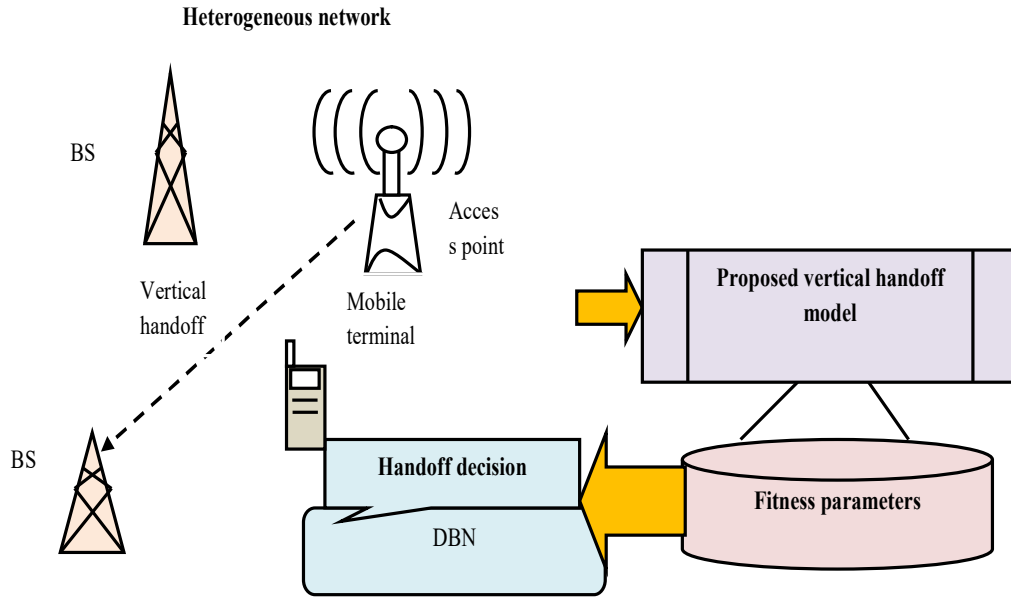


Fig.1. Block diagram of the adopted model for vertical handoff management

4. 1. Fitness Model

Initially, to aid the optimization network, the network starts taking into consideration of least networks with a limitless amount of networks. Moreover, the MN chooses the optimal network with minimum attribute outcome to choose a network. For the network, the attribute chosen is indirectly proportional to the network QoS. The adopted model fitness is modeled by taking into consideration of 5 attributes which include the loss of packet, energy, End to End Delay (E2E), jitter, BER, RSS out-of-hotspot probability of user moving into a hotspot, and ABR parameter. The fitness model of the adopted Hybrid GOA-GA algorithm is devised as,

$$\text{Fitness} = \sum_{\rho=1}^{\beta} D + F + R_i + C + \varepsilon + P_{\psi}, \text{RSS}, \text{ABR} \quad (5)$$

wherein, F stand for jitter, D stand for E2E delay, R_i stand for packet loss, ε stand for energy utilization, C stand for BER, and β stand for the total count of neighboring cells. This value relies on “0 to 1”.

i) E2E Delay

It indicates the time in which the data packet is transferred from sender to receiver. Generally, E2E is exploited to define the time for transmission of the packet. Here, the delay value must be minimum to obtain an enhanced transmission approach. In addition, the delay is stated as follows:

$$D = t_r - t_c \quad (6)$$

wherein, t_r represent time utilized to receive the packet from the server, as well as t_c represents the time utilized to transfer the first packet to the client.

ii) Jitter

It is exploited to determine the time variation of packets to arrive at the receiver. The jitter is happened because of route selection for packets to enter at network traffic, timing drift as well as destination, which is stated as follows:

$$F = \max_{k=2}^1 \left(\left| y(k) - y'(k-1) \right| - \left| y(k) - y(k-1) \right| \right) \quad (7)$$

wherein, $y(k)$ implies time utilized to transfer data, i implies chosen packets, $y'(k)$ implies time utilized to obtain data.

iii) Packet loss

It is a fundamental parameter that might affect the quality of the signal. The loss of a packet happens while beyond one data packet travel during network, however failed to attain receiver. By errors the

packet loss is produced that enclosed in the transmission of data that happens in wireless networks as well as reasons the congestion in the network, it is devised as,

$$\text{Packet loss}(R_i) = \frac{1 - S_x}{S_y} \quad (8)$$

wherein, S_y point out the sent packet and S_x point out packet received.

iv) Bit Error Rate

The BER is a function of SNR, and is assessed at the time of the Gaussian noise with arbitrary distribution as well as BER is devised as,

$$E = \text{Gaus}(\sqrt{\text{SNR}(o)}) \quad (9)$$

$$\text{SNR}(o) = \frac{\text{RSS}(o)}{I(o)} \quad (10)$$

wherein, $\text{Gaus}(z)$ symbolize Gaussian distribution which ranges among 0 to 1 and $I(o)$ symbolize the interference signal strength, and. o symbolize distance from terminal to BS.

$$\text{Gauss}(o) = \frac{1}{\sqrt{2\pi}} \int_0^{\infty} \exp\left(-\frac{y^2}{2}\right) dy \quad (11)$$

v) Energy consumption

To choose the networks the energy utilization is a vital attribute and it needs to be exploited carefully. By MN, the energy utilized is on the basis of the networks scanning of available networks in HO. The energy consumption formulation is indicated as,

$$\varepsilon = \sum_{u=1}^n \omega_i \times Q_u \quad (12)$$

wherein, Q_u indicate power required by MN to scan PoA in entrance network, as well as time utilized by an interface to scan data.

vi) Probability out-of-hotspot

The number of active users that travel through the hotspot is equivalent to the number of active users that travel on average in an equilibrium state [6] in the hotspot. Hence, the out-of-hotspot user probability who moves in the hotspot-i are indicated as follows:

$$P_{\psi} = \frac{\phi P_{\text{roam}}}{1 - \phi} \quad (13)$$

wherein, P_{roam} simplifies users roaming call probabilities ϕ simplifies macrocell users percentage which exists in hotspot-i.

vii) Received signal strength

At the receiving antenna, RSS [7] indicates the strength of the signal received calculated. In addition, the RSS is identified using the transmission power, distance calculated among the transmitter as well as receiver by taking into consideration of the radio environment. Moreover, the RSS is devised as,

$$\text{RSS}_v = -174 + (S_v / N_v) - 10 * \log_{10}(y) + 10 * \log_{10}(F_v * N_{\text{used}_v} / N_{\text{fft}_v}) + NF_v \quad (14)$$

where, NF symbolize the noise figure, (S_v / N_v) symbolize SNR, y symbolize distance interval, F symbolize frequency, N_{fft} symbolize FFT size, N_{used} symbolize a number of subcarriers.

viii) Available bit rate

ABR [7] is a service used in ATM networks in which sendersthe , as well as receiver, don't require to be synchronized. Here, ABR does not confirm data loss or delay. Moreover, the ABR technique allows the network to assign available bandwidth with ABR sources. Eq. (15) indicates the ABR, wherein, (S_v / N_v) symbolizes SNR X_v symbolizes network bandwidth.

$$\text{ABR} = X_v \times \log_2 \left(1 + \frac{S_v}{N_v} \right) \quad (15)$$

5. Adopted Technique

This section describes the adopted technique in a detailed manner. Initially, DBN is described then the Hybrid GOA-GA algorithm is explained.

5.1. DBN Model

The DBN [8] classifier is formulated by exploiting one MLP layer as well as two RBM layers. In the DBN classifier, no link subsists among hidden neurons and visible neurons. Additionally, the association is positioned among hidden as well as visible neurons. The input is fed to DBN classifier, which is considered as the fitness parameters named as *Fitness* and it is subjected to RBM layer-1 visible layer. The output via RBM layer-1 presents the input to RBM layer-2 so that output generated from RBM layer-2 is furthermore subjected as an input to MLP layer [12].

The input is subjected to hidden as well as a visible layer of RBM layer-1 is devised as,

$$x^1 = \{x_1^1, x_2^1, \dots, x_k^1, \dots, x_l^1\}; 1 \leq k \leq l \quad (16)$$

$$y^1 = \{y_1^1, y_2^1, \dots, y_o^1, \dots, y_p^1\}; 1 \leq o \leq p \quad (17)$$

wherein, l point out the total count of visible neurons, p point out the total count of neurons available in hidden layer x_k^1 point out k^{th} RBM layer-1 visible neuron, and y_o^1 point out o^{th} hidden neuron. Every neuron of the hidden, as well as a visible layer, comprises a bias. Hence, the 2 biases related to the neurons of both layer in RBM layer-2 is stated as eq. (18) wherein, h_o^1 point out o^{th} hidden neuron bias as well as g_k^1 point out k^{th} visible neuron bias. Hence, the RBM layer-1 weights are devised as eq. (20), wherein, w_{ko}^1 point out weight among k^{th} visible as well as o^{th} hidden neurons so that their weight vector size is stated as $[k \times l]$.

$$g^1 = \{g_1^1, g_2^1, \dots, g_k^1, \dots, g_l^1\} \quad (18)$$

$$h^1 = \{h_1^1, h_2^1, \dots, h_o^1, \dots, h_p^1\} \quad (19)$$

$$w^1 = \{w_{ko}^1\}; 1 \leq k \leq l; 1 \leq o \leq p \quad (20)$$

Hence, from hidden layer output produced of RBM layer-1 is calculated on basis of bias as well as weight connected with neurons and is devised as eq. (21), λ point out the activation function. Hence, the outcome attained from RBM layer -1 is devised as eq. (22).

$$y_o^1 = \lambda \left[h_o^1 + \sum_k x_k^1 w_{ko}^1 \right] \quad (21)$$

$$y^1 = \{y_o^1\}; 1 \leq o \leq p \quad (22)$$

In RBM layer-2, the learning process is developed based on outcome produced from the hidden layer of RBM layer-1 as well as outcome is similar as eq. (22). The RBM layer-s outcome is stated in the eq. (21) that is fed as an input to a visible layer of RBM layer-2. Therefore, in the visible layer, the amount of neurons is similar to the hidden layer neurons of RBM layer-1 as well as it is stated as eq. (23), wherein, $\{y_o^1\}$ indicates RBM layer-1 output. Therefore, RBM layer-2, the indication of the hidden layer is stated as eq. (24).

$$x^2 = \{x_1^2, x_2^2, \dots, x_p^2\} = \{y_o^1\}; 1 \leq o \leq p \quad (23)$$

$$y^2 = \{y_1^2, y_2^2, \dots, y_o^2, \dots, y_p^2\}; 1 \leq o \leq p \quad (24)$$

In RBM layer-2, the hidden, as well as visible layer biases, has same indication as shown in eq. (18) and eq. (19), however, they are indicated as g^2 as well as h^2 . Therefore, RBM layer-2 weight vector is indicated as eq. (25), wherein, w_{ko}^2 represent weight among k^{th} visible neuron as well as o^{th} hidden neuron so that weight size is indicated as $[v \times v]$, wherein, h_o^2 represents bias related with o^{th} hidden neuron.

$$w^2 = \{w_{ko}^2\}; 1 \leq k \leq l \text{ and } 1 \leq o \leq p \quad (25)$$

$$y_o^2 = \lambda \left[h_o^2 + \sum_k x_k^2 w_{ko}^2 \right] \forall x_k^2 = y_o^1 \quad (26)$$

Therefore, the hidden layer output attained is indicated as eq. (27). The aforesaid formulation is RBM layer-1 output, which is subjected as an input to MLP layer so that number of neurons relies on the input layer as p . Hence, MLP layer input is stated as eq. (28). wherein, s symbolizes the count of neurons enclosed in the input layer that is presented using RB layer-2 output $\{y_o^2\}$. Hence, MLP hidden layer is stated in eq. (29). wherein, X symbolizes the total count of neurons in the hidden layer. Suppose that F_X is the bias of X^{th} hidden neurons, wherein $X = 1, 2, \dots, Y$. Hence, the MLP layer is indicated as eq. (30),

wherein, T represent a total count of neurons enclosed in the output layer. The MLP layer consists of 2 weight vectors, in that one is among input as well as a hidden layer, in which the other is among the hidden as well as output layer.

$$y^2 = \{y_o^2\}; 1 \leq o \leq p \quad (27)$$

$$e = \{e_1, e_2, \dots, e_o, \dots, e_p\} = \{y_o^2\}; 1 \leq o \leq p \quad (28)$$

$$r = \{r_1, r_2, \dots, r_X, \dots, r_Y\}; 1 \leq X \leq Y \quad (29)$$

$$L = \{L_1, L_2, \dots, L_S, \dots, L_T\}; 1 \leq S \leq T \quad (30)$$

Suppose that w^A indicates weight amid input as well as hidden layers that is indicated as eq. (31), wherein, X^{th} hidden neuron so that w^A is $p \times Y$ size and w_{oX}^A implies weight among o^{th} input neuron. The hidden layer output is stated as eq. (32), wherein, V_X symbolizes hidden neuron bias as well as $e_o = y_o^2$, as input to MLP is outcome produced from RBM layer-2. Therefore, the weights among output as well as hidden layer are represented as w^B and are devised as eq. (33). Consequently, the output vector is computed by exploiting weight w^B as well as hidden layer output is stated as eq. (34), in which, r_X indicate the output of the hidden layer w_{XS}^B indicate weight among X^{th} hidden neuron and S^{th} output neuron.

$$w^I = \{w_{oX}^A\}; 1 \leq o \leq p; 1 \leq X \leq Y \quad (31)$$

$$r_X = \left[\sum_{o=1}^p w_{oX}^A * e_o \right] V_X \forall e_o = y_o^2 \quad (32)$$

$$w^B = \{w_{XS}^B\}; 1 \leq X \leq Y; 1 \leq S \leq T \quad (33)$$

$$L_S = \sum_{X=1}^Y w_{XS}^B * r_X \quad (34)$$

5.2 Hybrid GOA-GA Model

The Hybrid-GOA-GA integrates both advantages of GA as well as GOA methods [9]. It integrates the GOA exploration capability as well as GA exploitation capability; wherein GA operators (mutation as well as crossover) avert the adopted model from falling into local optima when GOA's process accelerates the search procedure as well as convergence to attain a global solution. In the adopted model, a solutions population is arbitrarily generated. In the optimization issue domain, these solutions are searched to attain optimal solutions using the GOA [11]. The solution evolution is performed using GA during this procedure.

a): Initialized an agent's population with arbitrary locations in search space as well as set GA and GOA parameters in d-dimensions. The preferred fitness model is estimated in d variables for each agent. Ascertain the target location as the best initial agent location.

b): The preferred fitness model is calculated in d variables for each agent. The target location T is updated as the optimal agent location found hitherto.

c): Tournament selection (TS) will be exploited in the adopted model; wherein a count of agents tour are selected arbitrarily from the population as well as an optimal agent from this group is chosen as a parent. This procedure is continued as frequently as agents should be selected.

-- Crossover:

The 2 agents, $A = [a_1, b_1]$ and $B = [a_2, b_2]$, are chosen as parents by TS. Let consider a as the crossover point for an exacting A and B, and the a-values in the off-springs are ascertained using the following equation:

$$\begin{aligned} a_{new1} &= (1 - \gamma)a_1 + \gamma a_2; \\ a_{new2} &= (1 - \gamma)a_2 + \gamma a_1 \end{aligned} \quad (35)$$

wherein γ represents an arbitrary count among 0 and 1. Directly from each parent, the residual parameter (b in this case) is inserted, therefore the new off-springs are:

$$\begin{aligned} \text{offspring}_1 &= [a_{new1}, b_1]; \\ \text{offspring}_2 &= [a_{new2}, b_2] \end{aligned} \quad (36)$$

Mutation: Each agent in a string is mutated $x_i \in [a_i, b_i]$ with mutation probability Pm by adding small arbitrary values on the basis of formulations as stated as follows:

$$X_i = \begin{cases} X_i + \Delta(t, b_i - X_i) & \text{if } \delta = 0 \\ X_i - \Delta(t, b_i - X_i) & \text{if } \delta = 1 \end{cases} \quad (37)$$

$$\Delta(t, y) = y \left[1 - r^{(1-t/T)^\beta} \right]$$

Wherein β indicates a positive constant selected randomly, r indicates a random number $r \in [0, 1]$.

Elitist scheme: The record of optimal agents directly reached into a novel set of agents is exclusiveness.

Evaluation: The preferred fitness model is estimated in d variables for each agent.

Updating: The target location is updated as the optimal agent location found hitherto.

d): Termination criterion: If the utmost count of generations is attained else agents converge, the adopted model will be halted. At last, the target location is set as the best solution.

6. Results and Discussions

The efficiency of the adopted model by exploiting the Throughput, delay, Energy consumption as well as Call drop, parameter by varying time as described in this section. Here, the proposed model was compared with the conventional models such as ABC, PSO, GA and DE.

Fig 2 demonstrates the performance analysis of approaches with delay, call drop probability, energy utilization parameter. In terms of delay, the proposed model is 21% better than the ABC; 15% better than the PSO, 24% better than the GA, and 25% better than the DE. Fig 3 exhibits the performance analysis of proposed and conventional approaches regarding throughput parameters. Here, the proposed model is 30% better than the ABC; 25% better than the PSO, 14% better than the GA, and 12% better than the DE. It is evident that the adopted model exhibited enhanced performance for vertical handoff management in the heterogeneous network from evaluation.

7. Conclusion

This work formulates the network-controlled vertical handoff in different, heterogeneous WSN taken into consideration of mobility technique. The adopted model carries out the management of vertical handoff on the basis of an effectual network selection strategy. Initially, if the rate was below the definite threshold, the sensor nodes verify the requirement of the data rate it starts the handover. By exploiting the effectual network chosen to model the vertical handoff management was carried out. An optimization model was exploited for the selection of the network model. In addition, the fitness model was formulated by exploiting definite metrics, which include energy utilization, BER, jitter, ABR, packet loss, Delay, hotspot probability, and RSS. To choose the optimal weights, the adopted Hybrid GOA-GA model was exploited to train the DBN. An optimal decision was performed to handle vertical handoff, network selection factors were considered as the input to adopted Hybrid GOA-GA -based DBN. Therefore, the adopted different model directs the vertical handoff in a different, heterogeneous network by exploiting the adopted Hybrid GOA-GA -based DBN. The adopted Hybrid GOA-GA -based DBN presented enhanced performance with minimum probability of delay, call drop, energy utilization as well as maximum throughput.

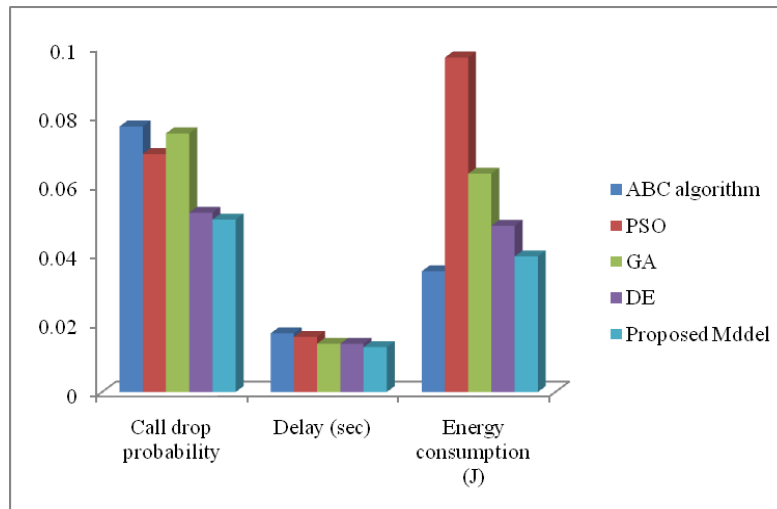


Fig.2. Analysis of adopted technique and conventional models

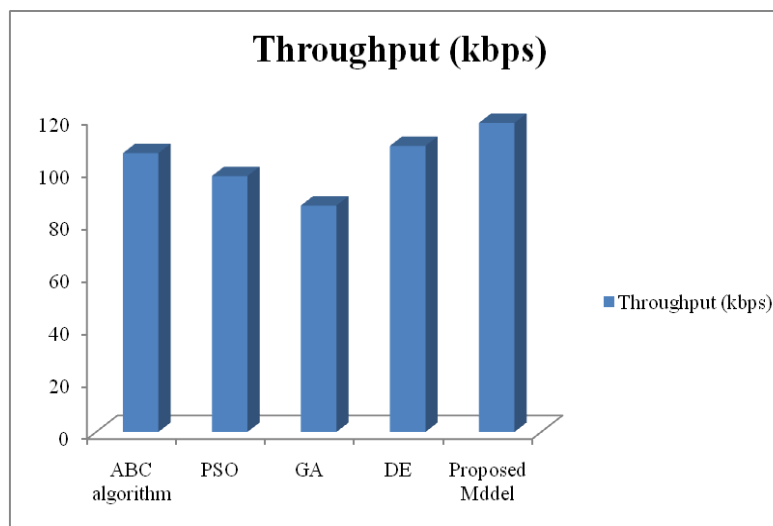


Fig.3. Analysis of adopted technique and the conventional models regarding the Throughput

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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