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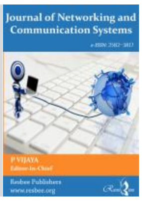

Vertical Handover Using Mutated-Salp Swarm Optimization Algorithm Based on Radial Basis Function Neural Network in Heterogeneous Networks

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Abstract: The heterogeneous network for a 4th generation, not constantly supports enhanced mobility and communication amid the Wireless Access Network. Therefore, the vertical handoff is extremely required. This work sets up a vertical handover that is context-aware via WiFi and WiMax in a heterogeneous environment. For the handover points, thriving handover shows enhanced purposes. Hence, an RBFNN-based network method to appreciate the network distinctiveness is initially elaborated. In the experimented environment, the RSS of the heterogeneous network is experimental to model the training library. In a heterogeneous network, to solve the handover points the trained network predicts RSS. To make sure the exact learning of the NN regarding the RSS network characteristics, a mutated Salp Swarm Algorithm (mutated-SSA) is proposed. The developed technique performance is validated using the conventional FF-NN, LM-NN, GWO-NN, and PSO-NN via handover, throughput, Mean Absolute Error, and predicted RSS analyses. For the developed mutated-SSA-RBFNN-based network model, the predicted RSS appears almost nearer to the actual model, obtaining effectual handoff.

Keywords: WIFI; RSS; RBFNN; Wimax; Heterogeneous Network; Optimization Algorithm

Nomenclature

Abbreviations	Descriptions
WAN	Wireless Access Networks
RBFNN	Radial Basis Function Neural Network
RSS	Received Signal Strength
WSN	Wireless Sensor Networks
FF-NN	Fire Fly-Neural Network
MN	Mobile Node
BS	Base Station
MNI	Maximum Number of Iteration
WIA	Wireless Internet Access
CLML	Collaborative Linear Manifold Learning
LM-NN	Levenberg–Marquardt-Neural Network
AP	Access Point
GWO-NN	Grey Wolf Optimization-Neural Network
LANs	Local Area Networks
WMN	Wireless Mesh Networks
DEA	Differential Evolution Algorithm
HIN	Heterogeneous Information Networks
PSO-NN	Particle Swarm Optimization-Neural Network
VHO	Vertical Handoff
MAE	Mean Absolute Error
AP	Access Points
LWPA	Improved Wolf Pack Algorithm
DV	Decision Variables
PSO	Particle Swarm Optimization
NS	Number of Salps
CLWPA	Clustering Routing Algorithm Based on Wolf Pack Algorithm
HDD	Heterogeneous Deep Diffusion
RSS	Received Signal Strength

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FF	Firefly
MIP	Mixed Integer Programming
XL	Lower Bounds
RODE	Relation-Oriented Deep Embedding
XU	Upper Bounds
4G	fourth generation

1. Introduction

WIA has to turn out to be a development using the progress of wireless communication technology. Anywhere anytime people desire to contain multimedia services. Nevertheless, these applications encompass the superior requirements of QoS. An MN encompasses to switch to additional AP because of the restricted coverage of a wireless network, while it moves out of the present AP [1]. During this process, there are handoffs and delays. For real-time services and VoIP this method is chiefly significant. Seamless mobile handoffs need continuous communications whilst an MN [16] is moving in the wireless networks. In real-time services provided that a seamless handoff is an important problem [15]. To evaluate handoff methods there are two important features such as packet loss rate and switching delay. Numerous works have paid attention to minimizing the packet loss rate and delay at the time of handoff.

WiMAX presents WIA to the subsequently level, and more than time, might attain alike rates to devices as WiFi [2]. WiMAX able to transport Internet access miles from the blanket large areas and the nearest WiFi hotspot named WANs, suburban, metropolitan, else rural using multi-megabit per Internet access and second mobile broadband [17]. Even though the wide-area Internet connectivity presented by 2.5 and 3G cellular data services are mobile, these services do not offer the broadband speeds to that users encompass turn out to be familiar and which WiMAX can transport. In most recent years, WiMAX encompasses recognized its significance as a substitute to cable and wired DSL, presenting a cutthroat broadband service presenting that can be quickly and cost-efficiently organized [3].

The wireless networks future generation encloses the incorporation of diverse wireless networks to hand out multiple users. Based on their applications, users access diverse wireless technologies like WMN, LANs, and cellular networks. While the user is itinerant one cell site to one more cell site networks, the connection from the primary cell site is ended and it is transferred to one more cell site called as handover or handoff. The handoff happens among the same networks are referred to as horizontal handoff and while the mobile node is moving arbitrarily in diverse directions over diverse networks is indicated as VHO. For the heterogeneous wireless networks are considered as examples are 4G wireless networks [4].

Generally, via the optimal access technologies, the network users are served, while server requires offering resources to new applications it offloads ingredient of 4G network traffic to the Wi-Fi network and offer sources to new applications. Nevertheless, the incorporation of multiple networks makes a difficult system plan and performance evaluation. It is surmounted using the precisely scheming mobility and the traffic control method exploiting resource management, position updating, and network planning [5].

The main contribution of the work is to propose a vertical handover with WiMax and WiFi in a heterogeneous network, by exploiting the mutated-SSA - RBFNN-based network model. Moreover, the paper examines the efficiency of the handoff by calculating the RSS. Moreover, the proposed method of performance compares conventional techniques.

2. Literature Review

In 2020, Chen Zhang et al [1], developed a RODE model for heterogeneous networks that discovers diverse associations between nodes. The captured associations were designed via node dissimilarity and similarity. Based on the dissimilarity and similarity, a multi-task Siamese NN was devised to carry out optimizes embedding representations and network embedding. Widespread evaluations have experimented on four heterogeneous networks.

In 2020, Wei Hu et al [2], developed a distributed analysis model that has a lot of possible benefits. In the alarm database, the main important feature was the vital decrease in the candidate set that be able to an immense amount help to develop the competence of alarm correlation algorithm in heterogeneous networks, thus additional minimizing the time needed for alarm correlation algorithm.

In 2020, Akash Anil and Sanasam Ranbir Singh [3], developed a measure in order to calculate the class inequity in HIN and study the class imbalance effects over two bibliometrics tasks, such as Author's research area classification and Co-authorship prediction, for DBLP dataset exploiting the node features produced using network embedding-based frameworks.

In 2020, Y.U. Xiu-wu et al [4], proposed a CLWPA for heterogeneous WSN. Initially, the finest heterogeneous nodes deployment was converted into a MIP issue. The estimated best solution of the issue was attained via the WPA that enhanced using levy flight and logistic function, subsequently, a heterogeneous network routing approach based on the LWPA was developed.

In 2019, Soheila Molaei et al [5], developed a new meta-path illustration learning algorithm, HDD, to use meta-paths as major entities in networks. Initially, the functional heterogeneous structures of the network were learned using an incessant latent illustration via traversing meta-paths with aspire of a global end-to-end perspective. Subsequently, the renowned deep learning models were used in produced features to forecast diffusion procedures in the network.

In 2020, JiaHui Liu et al [6], developed a new CLML approach. It can optimize the constancy of nodes similarities using the collaboratively exploiting the manifolds embedded among the target network and supplementary network. The experimentations were done in four benchmark datasets shown the stupendous benefits of CLML, not merely in maximum performance of prediction evaluated to baseline techniques, and ability to forecast the unidentified interactions in target networks precisely and efficiently.

3. Heterogeneous Network Modeling

3.1 System Model

For the user, the distribution of continuous service is the major cause to operate a handoff among two cellular networks. Initializing the handoff among two networks mostly it is based upon two basic principles, namely vertical handoff and a horizontal handoff. This work contributes to developing a handoff among two networks, that is, the WiMAX and the Wifi network.

Fig. 1 exhibits the schematic diagram to form the vertical and the horizontal handoffs among the WiMax and the WiFi networks. Actually, the horizontal handoff shows an association among homogeneous networks, while the vertical handoff shows an association among heterogeneous networks. The handoff gets place among two cells which have two diverse technologies in the vertical handoff process. Additionally, it can be represented as the node transmission among different WAN. The IP address and the technology might alter as the node travels from one network to an additional network. Hence, this procedure mainly concentrates on the modification of the network interface and the IP address.

3.2 Modeling of WiFi

The main concealed equipment of WLAN is the WiFi network. In the establishment, it encompasses presented services to a restricted count of users. Nevertheless, at present, the services encompass maximized, as the network performance contains also increases the utmost level. Essentially, the WiFi network engages AP and clients, and the network speed, are 108 Mbps. Nevertheless, there is a position of collision configuration, as WiFi communication is throughout the air. Consequently, the transmission of the data is extremely affected by numerous radio packets.

The power density minimization of the wave, whilst traveling during space is referred to as path loss. It is the dissimilarity among the transmitted and received powers. The WiFi network path loss for the distance divider model is exhibited in eq. (1), whereas, P_{L_0} indicates the path loss over a first meter, P_{L_1} indicates the path loss over distance d_{TR}, d_{BP} states the distance of the static breakpoint, d_{TR} states distance among the receiver and transmitter, and β_1 and β_2 states the distance power gradients which happen previous to after the breakpoints. The unit of P_{L_0} and P_{L_1} are dB, d_{BP} and d_{TR} states the meters and β_1 and β_2 are dB/meter.

$$P_{L_1} = P_{L_0} + \begin{cases} 10\beta_1 \log(d_{TR}), & d_{TR} < d_{BP} \\ 10\beta_1 \log(d_{BP}) + 10\beta_2 \log\left(d_{TR}/d_{BP}\right), & d_{TR} > d_{BP} \end{cases} \tag{1}$$

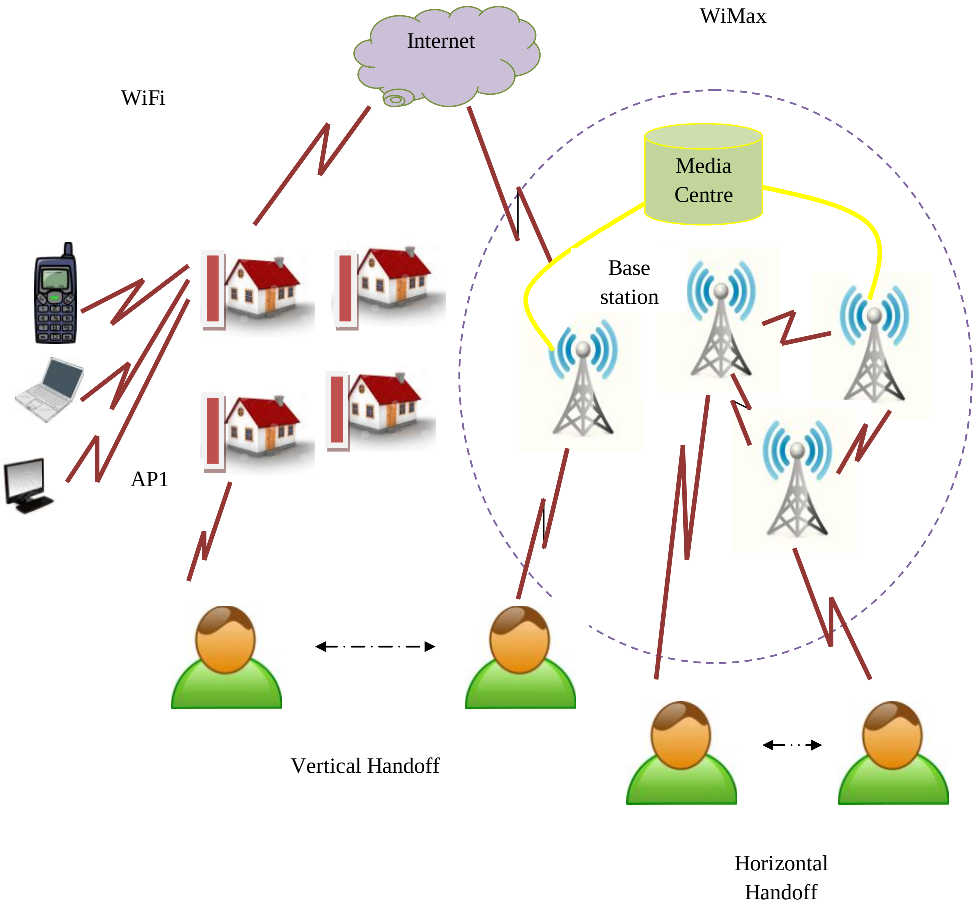

Fig. 1. *System model of horizontal and vertical handoff among WiFi and WiMax*

3.3 Energy Measure Modelling of WiMAX

WiMAX is a highly developed network that presents superior speed (70mbps) and coverage area than WiFi. Away from each other coverage area and speed, the advantage of WiMax lays on condition that capable bandwidth and minimized interference. WiMAX technology is referred to as safer, whereas transmission of data is throughout 2 channels, named downlink and the uplink. From the BS the data transmission to the user is performed by uplink and the transfer of data from the user to the BS via the downlink. Based on eq. (2), the WiMax network path loss model, whereas F shows the frequency in MHz.

$$P_L = 20\log_{10}(F) + 20\log_{10} d_{TR} + 32.45 \tag{2}$$

The entirety power of the received signal is called RSS. The complete RSS of WiMax and WiFi network is devised as path loss inverse that is exhibited in eq. (3).

$$R = \frac{1}{P_L} \tag{3}$$

4. Adopted Handover Decision Approach

4.1 Adopted RSS prediction

In [7], the RBFNN is a generally exploited NN by means of only one hidden layer. An RBFNN comprises three layers such as the hidden layer, input layer, and output layer. From the input layer to the hidden layer alteration is nonlinear. At output units, the output layer is linear and presents a summation. Fig 2 shows the model of RBFNN, whereas h hidden units, g input units, and o output units are in the RBFNN. $l = [l_1, l_2, ..., l_n]^T \in R^n$ indicates the input vector $W = R^{h \times o}$ indicates the output weight matrix, $b_1, ...b_0$ represents the output unit migration, $m = [m_1, m_2, ..., m_n]^T$ represents the output vector. $\psi_i = (\| l - c_i \|)$ represents i^{th} the hidden unit's Activation Function (AF). $\sum$ in the output unit states the output layer neurons exploit linear AF. Hence, the k^{th} output is indicated as $m_k = \sum_{i=1}^{k} \omega_i \psi_i (\| l - c_i \|)$, whereas ω_i represents the linked weight using that decision-makers provide the RBF. The important feature of the RBFNN, it uses the distance Euclidean distance function as the basis function and the RBF like Gaussian function as AF. In □-dimension space, the RBF is a radial symmetry regarding a center point. From the center point the farther the input neurons are aside from the minimum the level of the neuron activation. This feature of hidden units is named local quality.

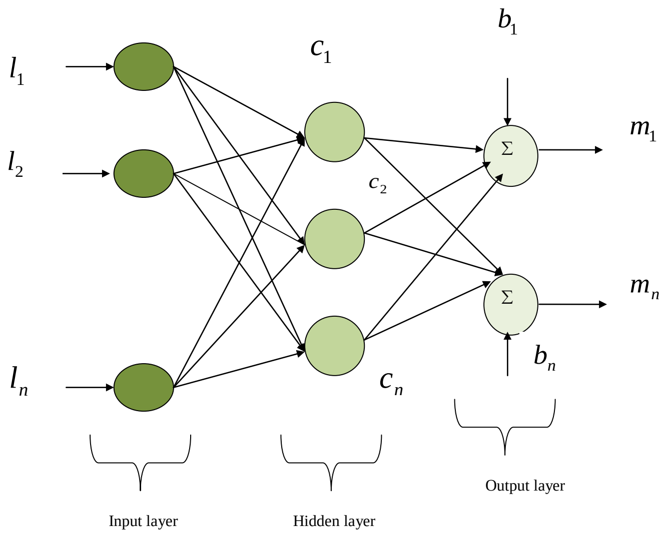

Fig. 2. *RBFNN model*

Hence every hidden unit has a center point c_i indicates the center point value of the i^{th} hidden unit; $(\| l - c_i \|)$ indicates the Euclidean norm that shows the distance from l to c_i. The RBF $\psi_i(\cdot)$ has several forms that are generally exploited as below,

Whereas, δ_l^2 is known as the spread of the BF [8]:

$$\psi_i(t) = e^{-\left(t^2/\delta_l^2\right)}, \text{ Gaussian function} \tag{4}$$

$$, \psi_i(t) = \frac{1}{1 + e^{-\left(t^2/\delta_l^2\right)}} \text{ reflected sigmoid function} \tag{5}$$

$\psi_i(t) = \frac{1}{\left(t^2 + \delta_l^2\right)^{\alpha}}, \alpha > 0$, inverse multiquadric function (6) Through continuous learning, RBFNNs functions are attained. As the NN property based upon network topology and connection weights among nodes, and the topological model is frequently selected based on particular applications, the RBFNN learning issue is to alter the connection weights among nodes. Weights can be decided by 2 techniques such as decided while RBFNN is modeled, and decided by learning (or training) based on the particular principles.

4.2 Proposed Mutated SSA

SSA is a type of Meta-heuristic approach which is recently proposed in [9]. The salps location is initially updated and subsequently the fitness of salps is computed and optimally salp is chosen as optimal salp between salps. Moreover, while the fitness of salp $i(\text{fit}(SP_i))$ is superior to the fitness of the $\text{bestsalp}(\text{fit}(F))$, it is chosen as the optimal salp for the future generation. The developed mutated SSA is as same as the SSA however while a salp is not chosen as $\text{bestsalp}(F)$ a mutation is used on it. In addition, for the future generation, if a salp is not chosen as optimal salp, it is mutated and subsequently is augmented to the population. For the future generation, this idea aids salps that have not had superior fitness to be selected as an optimal search agent can be mutated. Hence, the variety of the population is maximized and get away from local minima is reduced. There is a huge hand out of mutation approaches however in this work, the salps are mutated exploiting mutation of the DEA as shown below[10]:

$$SP_i = X_{r1} + F_m * (X_{r2} - X_{r3}) \tag{7}$$

In eq. (7), X_{r1}, X_{r2} and X_{r3} indicates 3 vectors that are arbitrarily chosen and F_m are constant-coefficient among [0, 2].

The procedure for Mutated-SSA are described as follows:

a) The population and parameter initialization: Initially, the approach parameters namely DV, XL, NS, XU, MNI and so forth are set. Subsequently, the population (salps) is produced among XU, and XL is stated in eq. (8).

$$SP_i^j = XL_j + (XU_j - XL_j) * rn[0,1] \quad i = 1,2,....., NS \quad j = 1,2,....., DV \quad (8)$$

b) Salps position updating: Initially, the location of the leader is updated and after other salps follow the leader and they make a chain. Eq. (9) is exploited to update the salps location.

$$SP_i^j = \begin{cases} F_j + p_1[(XU_j - XL_j)r_1 + XL_j] & r_2 \geq 0 \\ F_j - p_1[(XU_j - XL_j)r_1 + XL_j] & r_2 < 0 \end{cases} \quad (9)$$

In eq. (9), SP_i^j, F_j shows the leader's location (first salp) and the optimal search agent in the j^{th} dimension. r_1, and r_2 represents the arbitrary number among [0, 1]. c_1 represents the important parameter to update the leader and it is computed and it is shown in eq. (10).

$$p_1 = 2e^{-\left(\frac{4it}{MNI}\right)} \quad (10)$$

In eq. (10), MNI and it indicates the maximum number of iteration and current iteration, correspondingly.

The salp location i^{th} SP_i^j is updated based on the preceding salp as stated in eq. (11).

$$SP_i^j = \frac{X_j^i - X_j^{i-1}}{2} \quad (11)$$

c) Formulating the objective model: initially change the salp location i^{th} among XU and XL. Subsequently, estimate it based on the objective model.

d) Use the mutation: The fitness of salp i^{th} is evaluated by means of the optimal search agent (F). If salp i^{th} is superior to an optimal search agent (F), it can generally be believed. Conversely, a mutation is used on the salp location i^{th} as shown in eq. (12).:

$$SP_i = X_{r1} + F_m * (X_{r2} - X_{r3}) \quad (12)$$

In eq. (12), F_m indicates a constant coefficient among [0, 2]. X_{r1}, X_{r2} and X_{r3}, indicates three vectors that are arbitrarily chosen.

e) Termination circumstance: If $it < MNI$, the procedure from (b) to (d) is repeated, else the approach is halted.

f): Return F.

Algorithm: Proposed Mutated SSA

```
Initialize the salps population SP_i(i = 1,2,......., NS) between XU and XL
While itr<MNI
    Update p_1 using eq. (10)
        For each salp SP_i
            if (i == 1)
                    Position of the leader is updated using eq. (9)
            else
                    Position of the follower is updated using eq. (11)
            end
                    Alter the salps on the basis of the XU and XL variable bounds
                    Estimate the fitness fit of SP_i exploiting the objective function
            if fit (SP_i) < fit(F)
                    F = (SP_i)
            else
                    Apply mutation on (SP_i) for future generation using eq. (12)
                    Alter the (SP_i) on the basis of the XU and XL variable bounds
            end
        end
    end
Return F
```

5. Determination of Vertical Handover

Generally, numerous users are obtainable for network access. In concentration on an exacting mobile user, RSS is predicted by means of both loads and no-load balancing circumstances. Mobile user RSS is decided by separating it by totality count of users in the network in load balancing circumstance. On the other hand, the no-load circumstance might not regard as the other users. Hence, to decide the widespread RSS, the output from the NN model is calculated, if there is a required to enable or disable load. Eq. (11) indicates the mathematical formulation of widespread RSS, whereas N_u indicates the number of users.

$$\hat{R}_G = \frac{\hat{R}}{N_u}\left(w(1 - N_u) + N_u\right) \tag{13}$$

The 2 circumstances for deciding $\overline{R}_G$ are stated as below:

(a) If load balancing is enable $w = 1$

(b) If no load balancing $w = 0$

Theorem: The forecasted RSS exploiting the developed method represents balancing load conditions $w = 1$ and vice versa.

Proof: Consider the balanced load conditions that deal with the RSS of AP to all the obtainable users. Therefore,

$$R^{load} = \frac{\hat{R}}{N_u} \tag{14}$$

On the basis of the theorem, the widespread description of the predicted RSS is specified initial, as stated in eq. (15), whereas, $w = 0$ represents no RSS and $w = 1$ represents the balanced RSS.

$$\hat{R}_G = w\frac{\hat{R}}{N_u} \tag{15}$$

Besides together with the predicted RSS under no-load conditions,

$$\hat{R}_G = w\frac{\hat{R}}{N_u} + (1 - w)\hat{R} \tag{16}$$

$$= \hat{R}\left(w/N_u + (1 - w)\right) \tag{17}$$

$$= \frac{\hat{R}}{N_u}\left(w + (1 - w)N_u\right) \tag{18}$$

$$\hat{R}_G = \frac{\hat{R}}{N_u}\left(w(1 - N_u) + N_u\right) \tag{19}$$

6. Result and Discussion

6.1 Experimental Procedure

The developed model-based RSS prediction for the heterogeneous WiMax and WiFi network experimented in MATLAB and the experimentation outcomes were analyzed. In the network configuration, (WiMax, WiFi) is set as (5, 15), (7, 25), (10, 30), (12, 35), and (15, 40), whereas count of users has deviated from 30 to 100. Moreover, 1 mobile user is moved against the network for which widespread RSS was to be decided and the residual users were reserved static. The evaluation based on the handover, throughput, and RSS was performed and estimated. In the evaluation, the proposed-based model performance was evaluated with the performance of the existing methods such as GWO-NN [14], FF-NN [12], NN-LM [11], and PSO-NN [13] -based handover models to examine its performance.

6.2 Performance Analysis

Table 1, MAE is analyzed to examine how close predicted RSS is to actual RSS. Moreover, MAE is decided by measuring the dissimilarity among the predicted and actual RSS. For that reason, MAE of RSS that are predicted using the developed and the existing methods using the actual techniques. Hence, it is oblivious that the MAE of the developed model is minimum while comparing with the existing network methods; it leads to present an efficient vertical handover model.

Network configuration			Algorithms					
Wimax	WiFi	User	GWO-NN	FF-NN	LM-NN	PSO-NN	WOA-NN	Mutate-SSA-RBFNN
5	15	30	24414.84	42454.44	72441.44	22548.48	14448.04	13332.05
5	15	50	14241.27	24800.42	44188.24	15488.47	14544.48	12232.05
5	15	70	414450.7	447444.4	740450.4	420444.4	581871.7	401450.7
5	15	80	24548.54	40447.7	85245.04	40440.84	28185.44	22348.54
5	15	100	51504.54	40444.54	118084.4	48557.04	44444.44	108084.4
7	25	30	42180.08	44524.11	85474.48	24842.4	24752.82	22842.4
7	25	50	44424.48	57807.08	114154.5	44442.44	42071.4	40071.4
7	25	70	45724.17	54445.47	110544.4	42428.44	47115.54	40428.44
7	25	80	114424.5	124245.2	187047.2	111244.1	101444	100444
7	25	100	15447.44	22445.87	44424.85	14504.14	12451.14	10451.14
10	30	30	41420.28	44418.42	82841.41	28744.42	25844.47	25744.42
10	30	50	88508.74	45422.74	172102	84444.11	72454.44	42422.74
10	30	70	21847.24	24847.48	47542.22	18448.24	14418.24	19847.24
10	30	80	4442.145	4474.444	24812.01	1105.444	1445.485	1245.485
10	30	100	21724.47	24445.42	47724.44	17214.44	15424.42	13224.42
12	35	30	8440.014	11704.44	42785.44	5045.404	4224.084	10604.44
12	35	50	55848.41	40754.02	114144	50245.12	44484.08	31754.02
12	35	70	40781.54	44544.4	40444.4	28142.85	24024.41	22024.41
12	35	80	40444.07	44841.42	44445.7	45448.44	41440.8	36444.07
12	35	100	8124.425	10047.74	47544.71	4150.845	5004.85	4904.85
15	40	30	14581.11	17444.28	41548.7	10048.07	8454.514	8254.514
15	40	50	8244.782	4578.544	41044.57	4144.442	4524.017	7144.782
15	40	70	21444.44	24142.48	74142.44	20425.81	18487.45	16287.45
15	40	80	4400.774	4450.444	24255.08	1044.847	1854.427	1033.847
15	40	100	4242.845	14257.44	48014.41	5840.447	4488.044	4112.845

7. Conclusion

For the heterogeneous network with WiFi and WiMax, this work has developed a vertical handover model, by exploiting the mutated-SSA - RBFNN-based network model. Actually, RBFNN was exploited to obtain the knowledge concerning the network characteristics, to establish the handover points. Initially, heterogeneous network RSS was eminent and additional, the training library was modeled. Consequently, RSS was predicted by a trained network. Also, mutated-SSA optimization was exploited to make sure the accurate learning of the NN regarding the characteristics RSS of the network. Once experimented, the developed mutated-SSA model performance was evaluated using existing FF-NN, LM-NN, GWO-NN, WOA-NN and PSO-NN, methods. The throughput, handover predicted RSS, and MAE, was analyzed in the performance analysis. Hence, it experimented that the RSS predicted by the developed approach was superior to the conventional techniques, in provided that dominant handoff.

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