RAT Selection in Heterogeneous Wireless Networks Using a Hybrid Fuzzy-Enhanced Biogeography Based Optimization

Dr.S.Sangeetha[1], Dr.P.Shanthakumar[2]and S.Abirami[3],

[1]Assistant Professor, Department of CSE, Rathinam Technical Campus

[2]Professor, Department of CSE, Sri Subramaniya College of Engg. & Technology

[3]Research Scholar, Department of CSE, Karpagam Academy of Higher Education

Tamilnadu, India.

Abstract: RAT selection in heterogeneous wireless networks is to optimize the weight coefficients of multi-point decision making algorithm and ensure maximum user satisfaction ratio to select best RAT. For this a hybrid methodology integrating aEnhanced Biogeography Based Optimization (EBBO) is proposed. Thus the parallel fuzzy systems are employed to determine the probability of RAT selection, which acts as an input to the Enhanced biogeography based optimization procedure. Several experiments are carried out using the proposed EBBO – PFS technique to demonstrate the effectiveness and robustness in producing solutions compared to a few existing methods for RAT selection in heterogeneous wireless networks.

Keywords: Enhanced Biogeography Based Optimization, Radio Access Technology and Parallel Fuzzy System.

1. Introduction

In the current scenario, there is an extensive growth in the area of wireless mobile network systems. Fundamentally, the respective users of a wireless network have to be designated with the required number of radio resource units to communicate with the user to network links and from network to user links. The process of assigning required number of radio resource units to respective wireless networks is termed as multiple access technique. The tremendous utility of wireless modes has transformed the mobile communications from first generation to fifth generation to maintain the services rendered and guarantee on QoS (Quality of Service). Forthcoming modes of wireless communication will be based on Radio Access Technology selection and offered for the increasing heterogeneous systems.

It is to be noted that the respective user in a considered heterogeneous wireless network will be able to access the network services only with the help of available RATs. The RAT model of a heterogeneous wireless network is comprised of heterogeneous wireless network possesses two types of RAT – WLAN for local coverage logs and WWAN for global coverage logs. The coverage area logs of WLAN and WWAN are termed as micro cell and macro cell respectively. Based on the requirement of the end-users, the topology selection can be made to select the best RAT for the given heterogeneous wireless network

2. Survey of Literature

Sabbagh et al (2012) proposed an intelligent hybrid RAT selection approach for mobility optimization which includes sorting available RATs, collecting information on each RAT using the IEEE P1900.4 Protocol, and making decisions for selecting the most suitable RAT for incoming calls[4].

Seyed Heja Seyed Taheri, Shahin Jalili (2016) proposed algorithm is demonstrated by utilizing four benchmark truss design examples with frequency constraints. Numerical results show that the proposed EBBO algorithm not only significantly improves the performance of the standard BBO algorithm, but also finds competitive results compared with recently developed optimization methods. the overall performance of the standard BBO algorithm is enhanced by new migration and mutation operators[1].

S.Sangeetha&T. Aruldoss Albert Victoire (2015) proposed Non-Homogenous Biogeography Based Optimization (NHBBO) to optimize the weight coefficients of multi-point decision making algorithm and ensure maximum user satisfaction ratio to select best RAT. Thus the parallel fuzzy systems are employed to determine the probability of RAT selection, which acts as an input to the non-homogenous biogeography based optimization procedure[3].

K.Radhika,A.Venu Gopal Reddy (2011) proposed a network selection algorithm based on Fuzzy Multiple Attribute Decision Making. The algorithm considers the factors of Received Signal Strength(RSS), Monetary cost(C), Band Width (BW), Velocity (V) and user preference (P). It finds the Network selection function (NSF) that measures the efficiency in utilizing radio resources by handing off to a particular network. The network that provides highest NSF is selected as the best network to hand off from the current access network[2].

Sabbagh et al(2014)proposed an intelligent hybrid cheapest cost RAT selection approach which aims to increase users' satisfaction by allocation users that are looking for cheapest cost connections to a RAT that offers the cheapest cost of service. A comparison for the performance of centralized load- balancing, proposed and distributed cheapest cost and mobility optimization algorithms is presented[6].

Komal Mehta ; Raju Pal (2017) proposed an evolutionary based algorithm which improves the energy decay by using the improved BBO to elect cluster head. The simulation results shows the proposed algorithm enhance the stability and the lifespan of network in comparison of existing heterogeneous protocol such as LEACH, SEP, IHCR AND ERP[10].

Aymen et al (2014) proposed an approach for RAT selection algorithm developed by fuzzy logic and includes different criteria, assessing and making decisions, then selecting the most suitable technology. Simply, their role is to decide which of the available RATs is most suitable to fit the user to the best connection [5].

3. Rat Selection in Heterogeneous Wireless Networks Using a Fuzzy-EBBO

The proposed methodology developed for RAT selection in heterogeneous wireless networks. The proposed methodology employs parallel fuzzy systems for selecting the best RAT maximizing the user satisfaction rate. The key steps involved in the proposed approach is as follows: The five input parameters speed of the mobile terminal, received signal strength, network coverage, delay and data rate are employed for selecting the better access networks.

These input parameters are fed as input signals to parallel fuzzy systems. The outputs received from the parallel fuzzy systems are applied with that of the EBBO, which is used to optimize the weight coefficients in multi-point decision making algorithm for selecting the best radio access networks. Parallel fuzzy systems are employed rather than conventional fuzzy systems to reduce the complexity of inference rules. The three major procedures in proposed methodology are:

i) Design of a Parallel Fuzzy System (PFS) for the given input signals
ii) Formulating a Multi-point decision making algorithm with the metrics considered.
iii) Optimizing weight coefficients using proposed EBBO to determine the best RAT.

Figure 1 shows the block diagram of the proposed methodology that uses hybrid PFS – EBBO for selecting best RAT in heterogeneous wireless networks.

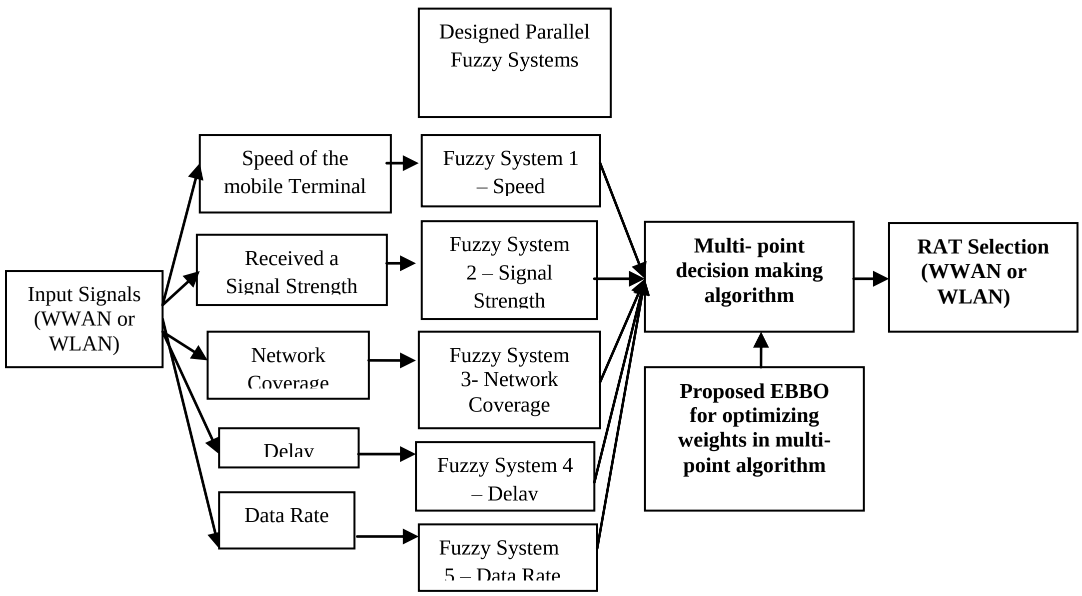

Figure 1 Block Diagram of Proposed Methodology for RAT Selection Using Hybrid PFS - EBBO

4. Design of Proposed Parallel Fuzzy Systems

Parallel Fuzzy Systems is designed for a heterogeneous wireless network model with two RATs, an IEEE 802.11g based WLAN and WCDMA (Wireless Code Division Multiple Access) based WWAN as shown in Figure 1. Each of the Fuzzy Systems for the considered 5 parameters results in a value related to the probability of selection of radio access network considered in the heterogeneous system. For each of the fuzzy system, Mamdani Fuzzy Inference System is adopted and mean of maximum method is used for carrying out defuzzification process. The membership functions employed for the input and output variables include triangular membership functions. Triangular membership function is used for both starting and ending regions of fuzzy variables (input and output) as well for the in-between regions of fuzzy variables (input and output).

5. Proposed Enhanced Biogeography Based Optimization

The standard Biogeography Based Optimization (BBO) algorithm suffers from premature convergence; furthermore, its weak exploration ability is an issue in some cases. The main reason for this poor exploration ability arises from its simple migration operator. In addition, the simple and purely random mutation operator of the BBO may lead to revisiting non-productive regions of the search space. In this study, in order to enhance the performance of standard BBO algorithm, new migration and mutation operators are proposed. These new migration and mutation operators improve the convergence properties of the BBO algorithm and enhance the algorithm's ability to further escape stagnation and premature convergence.In this paper, the proposed EBBO algorithm is applied over the multi-point decision making module to optimize the weight coefficients, so that the best WWAN and WLAN is selected. The optimal values of weight factors computed using the proposed EBBO algorithm plays a vital role in evaluating the equations (1)and (2), so that the algorithm searches to find the best RAT. Conventional Biogeography Based Optimization (BBO) consists of major two steps – migration and mutation. In the proposed EBBO, a migration operator, the immigrating habitat is updated by simply replacing one of the SIV(Suitability Index Variables)of emigrating habitat randomly, which often implies a rapid loss of diversity in the population. With the aim of achieving a better exploitation capability and providing efficient information sharing between the habitats, the new migration operator is proposed as follows:

$$H_i(SIV)\leftarrow H_i(SIV)+\Phi(H_j(SIV)-H_j(SIV))+\Phi(H_J^{best}(SIV)-H_i(SIV)) \qquad (1)$$

Where $\boldsymbol{H}_i$ (*SIV*) and $\boldsymbol{H}_j$ (*SIV*) are the immigrating and emigrating habitats, respectively, Φ is a random number uniformly generated between the 0 and 1, and $\boldsymbol{H}_j^{best}$ (*SIV*) denotes the best position experienced by the emigrating habitat. As it can be seen from (Eq.1), the new migration operator changes a variable of *i*th habitat by considering both current and best positions of the emigrating habitat. The proposed migration scheme has an important role in achieving efficient exploitation ability.

On the other hand, the purely random mutation operator of the standard BBO algorithm may lead to revisiting non-productive regions of the search space, which leads to weak exploration ability, excessive computational efforts, and long computing time. Therefore, in order to enhance the exploration ability and eliminate the effect of the purely random mutation, following mutation operator is proposed:

$$H_i(SIV)\leftarrow H_i(SIV)+N(0,1)\ (\frac{H_{max}(SIV)-H_{min}}{I_t}(SIV),I_{t=}1,2,..It_{max} \qquad (2)$$

where(0,1) is a random number generated according to a standard normal distribution with mean zero and standard deviation equal to one; $\boldsymbol{H}_{max}$(.) and $\boldsymbol{H}_{min}$(.) are the upper and lower bounds of the search space, respectively; *It* and It_{max} are the current iteration number and the maximum number of iterations, respectively. As it can be seen from (Eq.2), the size of the search space considered for the mutation procedure decreases with respect to time. It is worth mentioning that, whenever the mutated position of a habitat goes beyond its lower or upper bound, the habitat will take the value of its corresponding lower or upper bound.

For best RAT selection in a heterogeneous network, multi-point represents the various dimensions from which the RAT selection can be viewed. Each of the objectives in the multi-point decision making algorithm is to be assigned with suitable weights such that the best RAT is selected. With this fundamental idea, the weight function of the proposed multi-point decision making algorithm has the outputs of the proposed PFS and respective weight coefficients. The outputs from the proposed PFS are NO_1, NO_2, SSO_1, SSO_2, NCO_1, NCO_2, QoS_1 and QoS_2 for WWAN and WLAN. The evaluation of these output variables are carried out along with weight function. In general, the weight function of the proposed multi-point decision making algorithm is defined as,

$$W_k = \sum_{i=1}^{n} \frac{w_i o_{ik}}{n}, k = 1,2,\ldots,m \qquad (3)$$

Where, W_k – ranking value for each RAT k in a heterogeneous wireless network, w_i – weight coefficients for each input option, o_{ik} – individual output values from parallel fuzzy systems for that many number of RATs and n – total number of input parameters.

The ranking of the two considered RATs – WWAN and WLAN in this paper are given by,

$$W_{wwan} = \frac{(W_1 X N0_1)+(W_2 x SS0_1)+(W_3 X NC0_1)+(W_4 XQoS_1)}{n} \qquad (4)$$

$$W_{wwan} = \frac{(W_1 X N0_2)+(W_2 x SS0_2)+(W_3 X NC0_2)+(W_4 XQoS_2)}{n} \qquad (5)$$

In the above equations, w_1, w_2, w_3 and w_4 are the assigned weight factors for speed of the mobile terminal, signal strength, network coverage and quality of service respectively. The weighting factors are generally positive numbers in the range of [0, 1]. When a parameter is assigned with a highest weight, it is assumed to be a highest important objective. The maximum value of weighting factor is 1 and the minimum value of weighting factor is 0.1. On designing the multi-point decision algorithm, it is necessary to consider all the input parameters. The EBBO algorithm is proposed over the multi-point decision algorithm in order to optimize the weight coefficients that select the best RAT in a heterogeneous wireless network.

Fitness function formulation

The main aim of radio access technology network selection is to maximize the users percentage assigned to the networks possessing high signal strength. Hence, while formulating the fitness function which forms the core for the proposed EBBO, the received signal strength of the network is considered as the vital parameter. Equation (4) and (5) gives the weight function of WWAN and WLAN network respectively. The fitness function is formulated as the ratio of weight function of WLAN to weight function of WWAN. On evaluation when this value becomes greater than 1, then automatically the number of satisfied users is increased by one. Mathematically the fitness function is given by,

$$F = \frac{W_{wlan}}{W_{wwan}} \qquad (6)$$

Equation (6) is the fitness function employed in the proposed algorithm to determine the selection of best radio access networks between WWAN and WLAN.

6. EBBO Algorithm

Step 1: Initialization

The random habitats are generated in the search space as follows:

$H_i(SIV\text{-}H_i(SIV)+\Phi(H_j(SIV)\text{-}H_j(SIV))+\Phi(H_J^{best}(SIV)\text{-}H_i(SIV))$ (7)

where Φ is the random number uniformly distributed between 0 and 1. Then, the value of HSI or cost function value is calculated for each habitat.

Step2:Calculating immigration and emigration rates

In this step, the immigration $\lambda_i$and emigration $\mu_i$rates are calculated for each habitat based on the migration and HSI (Habitat Suitability Index) values.

$$\text{Prob(emigration from } H_j) = \frac{\mu_j}{\sum_{i=1}^{N} \mu_i}\text{, for } j=1,2,3..N_P \qquad (8)$$

Where N_P is the population size.

Step 3: Migration procedure

In the third step, the migration procedure is performed based on the immigration $\lambda_i$and emigration $\mu_i$rates for each habitat by utilizing (Eq. 1).

Step 4: Mutation procedure

After migration procedure, the variables of each habitat mutate with constant probability (*pMutation*) by (Eq. 2).

Step 5: Evaluation of HSI values

In this step, the HSI values of the new generated habitats are computed.

Step 6: Formation of new population of habitats

A specific number of elite habitats from the previous population ($KeepRate \times N_P$) are transferred to the current generation and combined with the new habitats. Finally, the habitats with high HSI values are selected from the combined population of habitats to form a new population.

Step 7: Finish or redoing

Repeat from Steps 2-6 until the stopping criteria is met and output the best solution.

Table 1. Sample Dataset of Mobile users for input parameters (N, SS, NC, δ&β)

S. No	N (WWAN & WLAN)	SS_1 (WWAN)	SS_2 (WLAN)	NC (WWAN)	NC (WLAN)	δ (WWAN & WLAN)	β (WWAN & WLAN)
1	0.985	-91.10	-94.392	8.236	1.750	356.869	265.062
2	8.944	-100.09	-71.701	5.166	7.027	281.502	92.153
3	5.409	-100.39	-57.327	6.797	0.366	711.129	249.829
4	1.202	-80.72	-67.569	5.251	3.258	590.609	264.175
5	4.151	-88.60	-85.056	1.807	2.554	476.555	139.514
6	6.537	-104.38	-58.816	9.326	1.635	451.341	96.362
7	5.774	-77.36	-65.267	4.400	2.576	715.045	342.473
8	0.642	-82.44	-93.567	7.673	6.712	281.508	292.420
9	4.191	-83.54	-72.897	3.908	8.161	137.763	334.689
10	7.891	-95.47	-64.273	8.523	5.056	138.602	235.284
11	4.440	-85.93	-57.455	0.600	8.668	366.157	322.704
12	6.068	-76.49	-93.443	4.860	8.913	503.781	195.838
13	0.185	-82.13	-82.177	8,214	4.447	877.049	141.257
14	9.218	-86.57	-65.403	7.382	1.763	449.444	385.412
15	9.169	-92.829	-58.227	4.103	8.937	42.298	389.183
and so on upto 1000 users							

Output of proposed PFS for considered mobile users

For the considered data samples of 1000 users with the sample data set as shown in Table 1, to start with proposed parallel fuzzy system (PFS) was applied and the fuzzy system output for the respective input parameters are computed. For generating fuzzy system outputs, Mamdani fuzzy inference system editor is used for the purpose. The degree of membership of the respective RAT selected for the given input variables with fuzzy rules evaluated will be the output of PFS module i.e., the output of PFS will be membership values (only between 0 to 1) of each of the input parameter considered. Table 1 shows the output of the Parallel Fuzzy System computed for the given input data. Only few samples of the outputs are shown in Table 1From Table 2, it is observed that NO_1, SSO_1, NCO_1 and QoS_1 indicate the probability of selection of WWAN network and NO_2, SSO_2, NCO_2 and QoS_2 indicate the probability of selection of WLAN network. The outputs from the PFS are sent to the Multi-point decision making algorithm – EBBO module to optimize the weighting coefficients and to select the best RAT for heterogeneous network.

Table 2.Computed Outputs of Parallel Fuzzy Systems

WWAN selection – Fuzzy Output				WLAN selection – Fuzzy Output			
NO_1	SSO_1	NCO_1	QoS_1	NO_2	SSO_2	NCO_2	QoS_2
0.125	0.625	0.875	0.541	0.331	0.331	0.125	0.541
0.875	0.125	0.651	0.411	0.625	0.625	0.780	0.627
0.676	0.125	0.766	0.625	0.875	0.875	0.125	0.375
0.125	0.875	0.665	0.625	0.727	0.727	0.347	0.375
0.452	0.625	0.125	0.375	0.625	0.625	0.253	0.875
0.751	0.125	0.875	0.572	0.875	0.875	0.125	0.427
0.706	0.875	0.489	0.782	0.778	0.778	0.257	0.375
0.125	0.875	0.824	0.482	0.365	0.365	0.761	0.659
0.457	0.875	0.421	0.375	0.625	0.625	0.875	0.668
0.858	0.125	0.875	0.375	0.776	0.776	0.633	0.875
0.495	0.768	0.125	0.548	0.875	0.875	0.875	0.550
0.725	0.875	0.583	0.625	0.370	0.370	0.875	0.375
0.125	0.875	0.875	0.625	0.625	0.625	0.496	0.375
0.875	0.722	0.805	0.625	0.756	0.757	0.125	0.375
0.875	0.625	0.445	0.375	0.875	0.875	0.875	0.625
0.875	0.125	0.125	0.375	0.625	0.625	0.125	0.875
and so on upto 1000 users							

Output from the Proposed EBBO Algorithm for RAT selection

The outputs from the proposed PFS are given as input to the multi-point decision making algorithm and EBBO part. The ultimate aim of the proposed EBBO algorithm is to optimize the weighting coefficients and select the best RAT. Employing the proposed EBBO algorithm, optimal weights are assigned to the parametric coefficients resulting in better user satisfaction ratio. The proposed EBBO is simulated for 25 trial runs with random values generated for the species generated and their control parameters. The optimal solution is arrived for the following settings of EBBO algorithm:

Maximum Generation - 210
Species Size - 45
Initial weights - Random generation

At the time of simulation, the ranges of users satisfied percentage is evolved and are tuned at the same time. Finally, the value of the percentage of satisfied users will be counted and based on that best RAT will be selected. Table 3 shows the optimal weighting factors user's satisfied percentage computed for the proposed Multi-point and EBBO algorithm.

Table 3.Optimal weighting factors of Proposed EBBO Algorithm

Number of Users	Optimal Weighting Factors				Percentage of Satisfied Users
	w_1	w_2	w_3	w_4	
100	0.5321	0.0651	0.1236	0.0611	91.21
200	0.4503	0.0874	0.1492	0.0713	91.06
300	0.6125	0.0765	0.1542	0.0983	90.42
400	0.5487	0.0712	0.1781	0.0533	91.01
500	0.4961	0.0643	0.1590	0.0620	91.15
600	0.7012	0.0697	0.1672	0.0781	91.29
700	0.6999	0.0702	0.1590	0.0654	91.06
800	0.5142	0.0842	0.1420	0.0716	91.09
900	0.6466	0.0737	0.1700	0.0645	91.26
1000	0.6124	0.0652	0.1287	0.0971	92.30

It can be noted from Table 3 that the proposed EBBO algorithm has evolved solution with an average percentage of user satisfaction being 92.3%. Table 5 shows the optimized solutions computed employing the proposed multi-point and EBBO algorithm. The ranking coefficients of WWAN and WLAN network are computed by the optimal weighting factors. The selection of best network is performed by comparing the ranking value computed for both the RAT networks.

Table 4. Optimal solutions for RAT selection using proposed EBBO

Ranking Value for WWAN for 100 users	Ranking value for WLAN for 100 users	Best RAT network selected based on Ranking Values
0.119	0.0609	WWAN
0.0496	0.1190	WLAN
0.0510	0.1296	WLAN
0.1559	0.1271	WWAN
0.1128	0.0965	WWAN
0.059	0.1367	WLAN
0.1640	0.1542	WWAN

0.1547	0.1498	WWAN
0.1462	0.1208	WWAN
0.1439	0.1567	WLAN
0.0515	0.0321	WWAN
0.1265	0.1175	WWAN
0.1638	0.1501	WWAN
0.1594	0.1432	WWAN
0.1443	0.1509	WLAN
And so on up to the set number of users		

Ranking values of the WWAN and WLAN are computed using the equations stated in equation (4) and equation (5) and are tabulated in Table 4. The optimal weights to compute the ranking factor is carried out using the proposed EBBO algorithm. Based on the ranking values computed best RAT (either WWAN or WLAN) is selected. Thus the proposed algorithm is employed to select the best RAT for the considered heterogeneous wireless networks.

Table 5.Comparison of Percentage of User's satisfaction rate of proposed hybrid PFS – EBBO approach and other methods

Sl.No	Methodology Adopted	Average percentage of User's satisfaction rate (%)	Computational time taken for selecting the best RAT (seconds)
1	Random Based Selection Approach	41%	190
2	Access Network Selection by Alkhawlani	79%	175
3	Mobile based RAT selection by Tudzarov	81%	160
4	Proposed Hybrid PFS – PSO Algorithm	87%	81
5	Proposed Hybrid PFS – KHA Algorithm	87.6%	82
6	Proposed Hybrid PFS – EBBO Algorithm	92.3%	84

From Table 5, it can be observed that the percentage of user satisfaction rate is better than that of the other methods considered for comparison. Also, the computational time taken for determining the best RAT for the given heterogeneous network is reduced to half the time in comparison with that of the methods available in the literature. Henceforth, it is noted that the proposed hybrid PFS – EBBO results in a user satisfaction rate of 92.3% within 84 seconds and proves to be better than any other methods considered for comparison.

7. Simulation Results

In this research, a heterogeneous wireless network with two types of radio access technologies of variant coverage ability is considered i.e., WWAN and WLAN. Around 100 to 1000 mobile users were considered with 100 users as increment point. The selection of best RAT (WWAN or WLAN) lies in the hand of the mobile users. Table 2 provides the sample data set of considered users with the constraint parameters fixed – speed of the mobile terminal, received signal strength, network coverage, packet delay and data rate, which are used for RAT selection process (1000 users were considered). The entire proposed algorithmic approach was rum in MATLABR2009 environment and executed in Intel Core2 Duo Processor with 3.27GHz speed and 3.00 GB RAM.

8. Conclusions

A more accurate approach to select best RAT is designed. Also, in case of heterogeneous networks, it is better to have an intelligent mechanism for selecting the network access. Considering the said factors, in this paper, the hybridization of Parallel Fuzzy Systems, Multi-point decision making algorithm and proposed Enhanced Biogeography Based Optimization is devised to select a best RAT with a higher user's satisfaction rate. From the results computed based on the simulations carried out for the considered number of mobile users, it is observed that the proposed hybrid PFS – EBBO approach performs better with the other methods employed for RAT selection .The computational experiments show that the presented EBBO algorithm can get better solutions, and it is more efficient than the standard BBO algorithm.

9. References

1.*Seyed Heja Seyed Taheri,Shahin Jalili,"Enhanced Biogeography based optimization: A New Method for Size and Shape Optimization of Truss Structures with Natural Frequency Constraints", Latin American Journal of Solids and Structures*Print version *ISSN 1679-7817*,On-line version, *ISSN 1679-7825 Lat.Am.j.solids struct. , vol.13 No.7(2016), Riode Janeiro.*

2.*K.Radhika,A.Venu Gopal Reddy,'Network selection in heterogeneous wireless networks based on Fuzzy Multiple criteria Decision Making',3rd International Conference on Electronics Computer Technology(2011).*

3.*S.Sangeetha&T.Aruldoss Albert Victoire,"Radio Access Technology Selection in Heterogeneous Wireless Networks Using a Hybrid Fuzzy-Biogeography Based Optimization Technique",Wireless, volume 87, 2016pages 399–417.*

4.*AL.Sabbagh, A, Braun, R &Abolhasan, M, "A power efficient RAT selection algorithm for heterogeneous wireless networks", In Communications and Information Technologies (ISCIT), IEEE International Symposium on, (2012),pp. 997-1002.*

5.*Aymen,BZ,Ayadi,M&Tabbane.S,"A fuzzy logic algorithm for RATs selection procedures.In Networks, Computers and Communications", International Symposium on,(2014),pp. 1-5.*

6.*Sabbagh,AA, Braun, R & Abolhasan, M , "Intelligent Hybrid Cheapest Cost and Mobility Optimization RAT Selection Approaches for Heterogeneous Wireless Networks", Journal of Networks, Vol.9, no. 2, (2014),pp. 297-305.*

7.*J.J.Escudero-Garzas and C. Bousono-Calzon, "An Analysis of the Network Selection Problem for Heterogeneous Environments with User-Operator Joint Satisfaction and Multi-RAT Transmission",* Wireless Communications and Mobile Computing,*(2017) vol. 2017.*

8.*Qing He, "A Fuzzy logic based vertical handoff decision algorithm between WWAN and WLAN",* Proceedings of International Conference on Networking and Digital Society, *(2010),pp. 561-564.*

9.*Hasib;Abraham,"A Simulation Framework for Performance Evaluation of Network Selection Algorithms in Heterogeneous Wireless Networks", IEEE 72nd Vehicular Technology Conference,(2010).*

10.*Komal Mehta , Raju Pal, "Biogeography based optimization protocol for energy efficient evolutionary algorithm: (BBO: EEEA)", International Conference on Computing and Communication Technologies for Smart Nation (IC3TSN) (2017).*