KSII TRANSACTIONS ON INTERNET AND INFORMATION SYSTEMS VOL. 6, NO. 7, July 2012

Network Selection Algorithm for Heterogeneous Wireless Networks Based on Multi-Objective Discrete Particle Swarm Optimization

Wenzhu Zhang[1], Kyung Sup Kwak[2] and Chengxiao Feng[1]
[1] State Key Lab. of Integrated Service Networks, Xidian University
Xi'an, Shaanxi 710071, P. R. China
[2] School of Information and Communication Engineering, Inha University
Incheon, 402-751, Korea
[e-mail: wzzhang1@mail.xidian.edu.cn, fengcx1988@hotmail.com, kskwak@inha.ac.kr]
*Corresponding author: Wenzhu Zhang

Received May 4, 2012; accepted July 2, 2012; published July 25, 2012

Abstract

In order to guide users to select the most optimal access network in heterogeneous wireless networks, a network selection algorithm is proposed which is designed based on multi-objective discrete particle swarm optimization (Multi-Objective Discrete Particle Swarm Optimization, MODPSO). The proposed algorithm keeps fast convergence speed and strong adaptability features of the particle swarm optimization. In addition, it updates an elite set to achieve multi-objective decision-making. Meanwhile, a mutation operator is adopted to make the algorithm converge to the global optimal. Simulation results show that compared to the single-objective algorithm, the proposed algorithm can obtain the optimal combination performance and take into account both the network state and the user preferences.

Keywords: Heterogeneous wireless networks, network selection algorithm, particle swarm optimization, multi-objective decision-making, elite set

This work was supported in part by the State Key Development Program for Basic Research of China under grant No.2009CB320404, and in part by the National Natural Science Foundation of China under grant No.61072068. This work was also supported in part by the program for Cheung Kong Scholars and Innovative Research Team in University under grant No.IRT0852, and in part by the National Research Foundation of Korea grant funded by the Korea government (MEST) No.2010-0018116.

http://dx.doi.org/10.3837/tiis.2012.07.005

1. Introduction

With rapid development of communication technologies and applications, the future wireless network will be a wireless convergence network consisting of various wireless access technologies which work collaboratively to bear service. These heterogeneous networks have good complementary characteristics in terms of coverage, resource management and service support[1]. As one of the key technologies of resource management in heterogeneous wireless networks, network selection algorithm is the important premise to guarantee that the network resources are used optimally and the mobile users maintain the best connection status. Therefore, it has become a hot issue in the research of heterogeneous wireless networks[2][3].

Among all the proposed network selection algorithms currently, we can find quite a few algorithms based on different criterias. A queuing model and an efficient cell selection algorithm are proposed in [4], which can achieve a load balancing between neighboring cells and minimize handover failure. [5] presents a two phase radio access technologies selection strategy based on network load and SIR for CDMA-OFDMA heterogeneous networks, which can not only balance the network load, but also improve the SIR significantly. To maximizing the network throughput, an active access point selection algorithm is presented in [6]. What's more, some algorithms based on artificial intelligence have also been proposed. Population evolution and reinforcement-learning algorithms for network selection are proposed in [7] which are based on the theory of evolutionary games, and an network selection algorithm based on reinforcement learning is obtained in [8] which selects the best network with considering not only the current network load but also the potential future network states. But all the algorithms mentioned above only consider one objective so that they can't satisfy the increasingly requirements of the operators, users and the Quality of Service (Quality of Service, QoS). Recently, there have also been put forward some new network selection algorithms which are based on multi-objectives[9][10][11], but these algorithms can only rely on changing the weights of the targets artificially to get better results. So these algorithms can not adapt to the variety of changes in the network environment well for their subjective characteristics.

In this paper we propose a network selection algorithm which is based on multi-objective discrete particle swarm optimization (Multi-Objective Discrete Particle Swarm Optimization, MODPSO). It considers different accessing objectives comprehensively, so that it can provide a reasonable selection of networks for users. Moreover, the algorithm converges fast and is adaptable.

The rest of this paper is organized as follows. In Section 2, we present the network selection model. Section 3 presents the network selection algorithm which is based on multi-objective discrete particle swarm optimization. Given the heterogeneous network environment, Section 4 makes use of MODPSO we put forward to select a network to access and the optimal combination performance is obtained. Section 5 gives a summary of the paper.

2. Network Selection Model

Fig. 1 depicts a heterogeneous network which consists three radio access networks, which are WLAN, TD-LTE and WiMAX. Each of the three radio access networks, WLAN, TD-LTE and WiMAX, represents one radio access technology respectively. The coverage area of different radio access network is different and overlaps. A terminal with multi-mode can access anyone of the networks related and obtain services in the overlapping area. A centralized radio resource manager obtains the status information of each radio access network and terminal through the Internet first, and then it processes resources coordination and joint management. When a terminal accesses or requests for handover, the manager triggers the MODPSO algorithm. It will provide the user with the accessing option whose objectives are to optimize the radio resource's utilizing, to maximize the QoS, etc.

Suppose that there are M access networks in the area and N users request to access or for handover at a certain moment, then the network selection model can be abstracted as a multi -objective constrained optimality problem. It includes an available matrix $\boldsymbol{L}$, an access matrix $\boldsymbol{X}$, objective function vectors $F(\boldsymbol{X})$ and constraints.

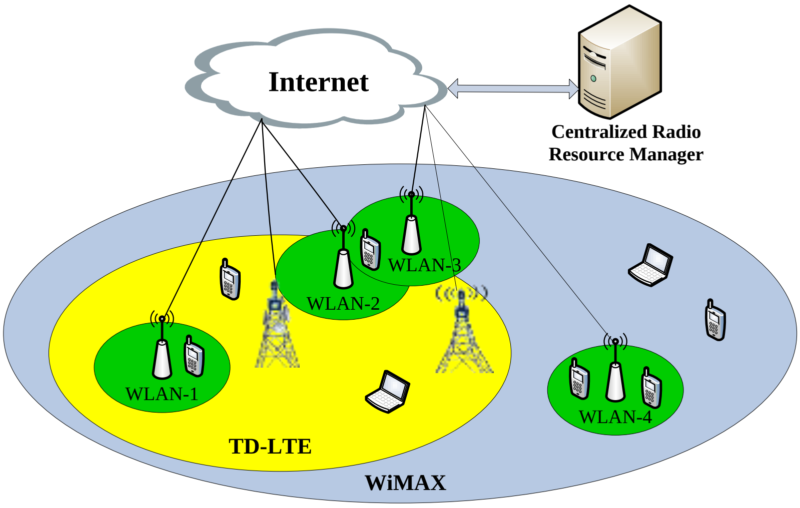

Fig. 1. Network Selection Model

(1)Available matrix $\boldsymbol{L}=\{l_{nm} \mid l_{nm} \in 0,1\}_{N\times M}$, among which $l_{nm}=1$ indicates that the network m is available to the user n; otherwise $l_{nm}=0$.

(2)Access matrix $\boldsymbol{X}=\{x_{nm} \mid x_{nm} \in 0,1\}_{N\times M}$, among which $x_{nm}=1$ indicates that the user n accesses to the network m; otherwise $x_{nm}=0$.

(3) $\boldsymbol{F}(\boldsymbol{X})$ is an vector composed by k objective functions, which represents objectives required to be optimized, such as the network load, the user's satisfaction, and so on;

(4) Constraints represent restrictive factors. For example, each user can only access one network, and the access matrix must accord with the available matrix, etc.

The constrained optimality task can be expressed as follows:

$$\begin{cases} \max \boldsymbol{F}(\boldsymbol{X}) = \max(f_1(\boldsymbol{X}), f_2(\boldsymbol{X}), \cdots, f_K(\boldsymbol{X})) \\ \sum_{m=1}^{M} x_{nm} - 1 \le 0 \qquad n=1,2,\cdots,\mathrm{N} \\ x_{nm} - l_{nm} \le 0 \qquad n=1,2,\cdots,N;\ m=1,2,\cdots,M \end{cases} \tag{1}$$

Then we transform the original constrained optimization task into an unconstrained optimality problem by adopting the penalty function method, which is as follows:

$$R_i\left(\boldsymbol{X},\sigma\right)=f_i\left(\boldsymbol{X}\right)-\sigma\left(\sum_{n=1}^{N}\max\left\{\sum_{m=1}^{M}x_{nm}-1,0\right\}+\sum_{n=1}^{N}\sum_{m=1}^{M}\max\left\{x_{nm}-l_{nm},0\right\}\right),\quad (i=1,2,\cdots,K) \tag{2}$$

$$\max\boldsymbol{F}\left(\boldsymbol{X}\right)=\max\left(R_1\left(\boldsymbol{X},\sigma\right),R_2\left(\boldsymbol{X},\sigma\right),\cdots,R_K\left(\boldsymbol{X},\sigma\right)\right) \tag{3}$$

σ is a positive constant which is called the penalty parameter whose value is large enough[12]; and $\boldsymbol{F}\left(\boldsymbol{X}\right)$ acts as the fitness function in MODPSO algorithm.

3. Network Selection Algorithm Based on MODPSO

3.1 The Basic Idea of MODPSO Algorithm

The particle swarm optimization (Particle Swarm Optimization, PSO) is a kind of evolutionary algorithm which has been developed in recent years. It was proposed by Kennedy and Eberhart[13] based on a social psychological model of social influence and social learning[14]. Each individual in the particle swarm follows a simple action, that is to follow the example of the successful experiences of neighboring individuals, but the cumulative behavior demonstrated is to research the best area in a high-dimensional space. The PSO does not need the gradient information of the objective function and can achieve a good balance between the global searching ability and the local searching ability. PSO has been found to be successful in a wide variety of optimization tasks, such as function's optimization, neural network training, fuzzy system control, as well as other genetic algorithm applications in the field.

A PSO algorithm maintains a population composed of a certain number of particles, in which each particle represents a potential solution of the problem. In this paper, each particle represents an access matrix $\boldsymbol{X}$. The particles fly in the multi-dimension space and they adjust their positions relying on their own experience as well as the experience of the neighbors. $\boldsymbol{X}_i\left(t\right)$ represents the position of particle i at time t, and $\boldsymbol{V}_i\left(t\right)$ represents the speed vector at time t. The speed vector is the power to drive the entire optimization process, which reflects the particle's prior knowledge and the interaction information from its neighbors. Its update formula is as follows[15]:

$$v_i^{nm}(t+1)=wv_i^{nm}(t)+c_1r_1[pbest_i^{nm}(t)-x_i^{nm}(t)]+c_2r_2[gbest_i^{nm}(t)-x_i^{nm}(t)] \tag{4}$$

In formula (4), $x_i^{nm}(t)$ represents the component of vector $\boldsymbol{X}_i(t)$ in the direction of $\left(n,m\right)$, and $v_i^{nm}(t)$ represents the component of vector $\boldsymbol{V}_\mathrm{i}(t)$ in the direction of $\left(n,m\right)$; $pbest_i^{nm}(t)$ is the component of vector $\boldsymbol{PBest}_i$, which denotes the best position of that particle i visited so far, in the direction of $\left(n,m\right)$; $gbest_i^{nm}(t)$ is the component of vector $\boldsymbol{GBest}$, which represents the globally best position, in the direction of $\left(n,m\right)$; w is the particle's inertia weight; c_1 is the local position constant while c_2 is the global position constant, whose values are usually one, and they play a role in accelerating the searching speed; r_1 and r_2 play a role in enhancing the algorithm's randomness, whose value are uniformly distributed in [0,1].

We update a particle's position by using its speed. Since the element in the particle's position $\boldsymbol{X}_i(t)$ can only be 0 or 1, we can use discrete particle swarm optimization (Discrete Particle Swarm Optimization, DPSO) algorithm's position updating strategy[15]. First, we normalize the speed by using function $S(\cdot)$:

$$S\left(v_i^{nm}(t+1)\right)=[1+\exp(v_i^{nm}(t+1))]^{-1} \tag{5}$$

Function $S(\cdot)$ owns the following characteristics:

$S(v)\in(0,1)$

$S(0)=0.5$

$\lim\limits_{v\to\infty}S(v)=1$

$\lim\limits_{v\to-\infty}S(v)=0$

So we can get the position updating formula by using formula (5):

$$x_i^{nm}(t+1)=\begin{cases}1, & r_3<S\left(v_i^{nm}(t+1)\right)\\ 0, & otherwise\end{cases} \tag{6}$$

r_3 is a random number uniformly distributed in [0,1]. Now $v_i^{nm}(t+1)$ becames the probability that the value of $x_i^{nm}(t+1)$ is 0 or 1. For example, if $v_i^{nm}(t+1)=0$, then $prob(x_i^{nm}(t+1)=1)=50\%$, from which we can get the particle's position $\boldsymbol{X}_i(t+1)$ of the next time.

Different from single-objective optimization, it requires meeting two or more objectives in the multi-objective optimization. There may be conflicts and Ramsay Rule among the multiple objectives. To solve this problem, we often find a series of optional solutions which are optimal in the sense of compromise, and then choose the best one from the optimal solutions according to certain rules. Before putting forward the algorithm proposed in this paper, we introduce several basic concepts in multi-objective optimization.

(1)Dominance: A decision vector $\boldsymbol{X}_1$ dominates another decision vector $\boldsymbol{X}_2$ which is denoted as $\boldsymbol{X}_1\prec\boldsymbol{X}_2$, if and only if $\boldsymbol{X}_1$ is not worse than $\boldsymbol{X}_2$ in each objective. That is to say, $f_k(\boldsymbol{X}_1)\geq f_k(\boldsymbol{X}_2)$, $\forall k=1,2,\cdots,K$ and $\boldsymbol{X}_1$ is strictly better than $\boldsymbol{X}_2$ in at least one objective. In other words, $\exists k=1,2,\cdots,K$ to make $f_k(\boldsymbol{X}_1)>f_k(\boldsymbol{X}_2)$;

(2) Non-dominated solutions: decision vector set $[\boldsymbol{X}_1,\boldsymbol{X}_2,\cdots,\boldsymbol{X}_1]$ is a non-dominated solution means that none of the vectors in the set dominates any other vectors. The subscript I is the number of dominated vectors.

(3)Pareto optimal: a decision vector $\boldsymbol{X}^*$ is Pareto optimal if there doesn't exist $\boldsymbol{X}\neq\boldsymbol{X}^*$ to dominate it.

(4) Pareto optimal set: All the Pareto optimal decision vectors form the Pareto optimal set $\boldsymbol{P}^*$.

(5) Pareto optimal front: Given the objective function vector $\boldsymbol{F}(\boldsymbol{X})$ and Pareto optimal set $\boldsymbol{P}^*$, the Pareto optimal front is defined as:

$$\boldsymbol{PF}^* = \{\boldsymbol{F} = (f_1(\mathbf{X}^*), f_2(\boldsymbol{X}^*), \cdots, f_K(\boldsymbol{X}^*)) \,|\, \boldsymbol{X}^* \in \boldsymbol{P}^*\} \tag{7}$$

The purpose of solving the multi-objective problem is to estimate the real Pareto optimal front, then choose the best trade-off result.

Instead of getting only one optimal solution, a particle gets a group of optimal solutions when it updates each time in the MOFPDO algorithm proposed, which is different from the single-objective PSO algorithm. What's more, there is non-dominated relationship between any two particles. So it becomes very important to guide the particle to "flight" by selecting a particle that is from the best population and owes the best position in that it visited so far from a group of non-dominated solutions set. By adopting the strategy of updating "Elite set" and increasing the diversity of a population, we improve the multi-objective optimization method presented in [16] and proposed the MOFPDO algorithm.

The main function of the elite set is to keep the historical record of the non-dominated solutions in the searching process and provides the global optimal solution. The updating rules for the elite set are shown in **Fig. 2**. If the elite set is empty, a new particle $\boldsymbol{X}_i$ can be put into elite set directly; if there is a particle that dominates $\boldsymbol{X}_i$ in the elite set, $\boldsymbol{X}_i$ can not be put into the elite set; if $\boldsymbol{X}_i$ does not dominate the particle in elite set and vice versa, $\boldsymbol{X}_i$ can be put into the elite set; if $\boldsymbol{X}_i$ dominates some of the particles in the elite set, put $\boldsymbol{X}_i$ into the elite set and delete the particles dominated by $\boldsymbol{X}_i$. We select a particle as the global optimum ***GBest*** from the elite set by using the grid roulette selection method[16].

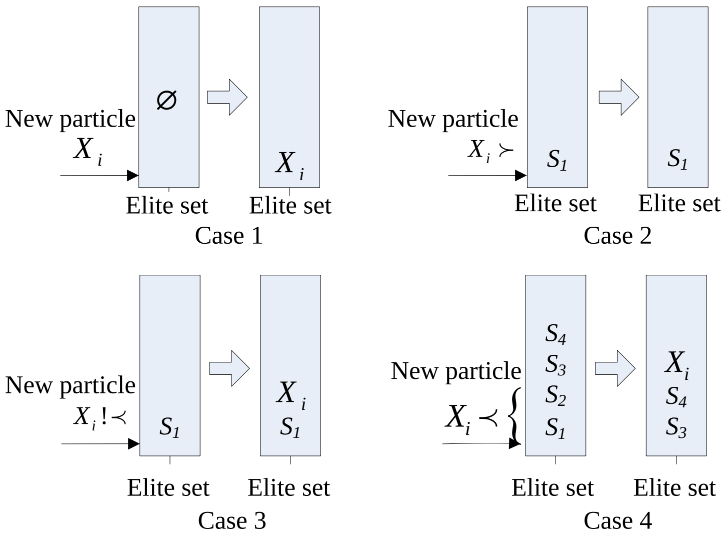

Fig. 2. The strategy to update an Elite set

PSO algorithm converges fast which may lead it converge to a false Pareto front[16], that is, it may converges to a local optimum in some multi-objective optimization tasks. This motivated the development of a mutation operator that tries to explore with all the particles at the beginning of the search. Learning from [17], we introduce a mutation operator

$\delta, \delta \in [0,1]$. The mutation operator δ is able to change the variety probability of inferior particles and superior particles in the iterative process. It can make superior particles vary with the small probability while inferior particles vary with random assignment so as to improve the population's diversity. Combining with the traditional PSO algorithm, we can get the particle's speed updating formula:

$$v_i^{nm}(t+1)=\begin{cases} wv_i^{nm}(t)+c_1r_1[pbest_i^{nm}(t)-x_i^{nm}(t)]+c_2r_2[gbest_i^{nm}(t)-x_i^{nm}(t)], if\ \boldsymbol{X}_i(t)\in \boldsymbol{Elite\ set} \\ \delta v_i^{nm}(t)+c_1r_1[pbest_i^{nm}(t)-x_i^{nm}(t)]+c_2r_2[gbest_i^{nm}(t)-x_i^{nm}(t)], if\ \boldsymbol{X}_i(t)\notin \boldsymbol{Elite\ set} \end{cases} \tag{8}$$

δ is a random number distributed in [0,1].

3.2 The Specific Process of MOFPDO Algorithm

The flow chart of the network selection algorithm, that is MODPSO algorithm proposed in this paper, is shown in **Fig. 3**.

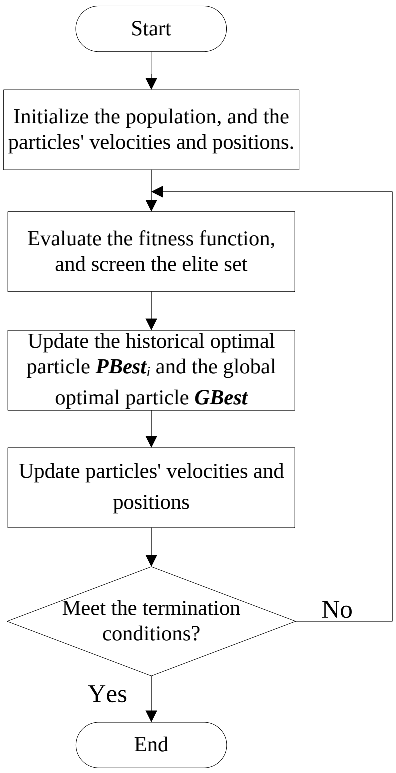

Fig. 3. Flow chart of MODPSO algorithm

Step 1: First, a random population is generated, and the size of this random population is I. That is, there are I access matrixes been generated randomly which are consistent with the constraints. These matrixes are considered as the particles' positions and denoted by $\boldsymbol{X}_1(t), \boldsymbol{X}_2(t), \cdots, \boldsymbol{X}_I(t)$. Set $t=0$, initialize particle i's speed $\boldsymbol{V}_i(0)$ randomly, and denote its initial position $\boldsymbol{X}_i(0)$ by $\boldsymbol{PBest}_i$; selected at least two particles randomly as the initial elite set at the same time.

Step 2: For each access matrix $\boldsymbol{X}_{\mathrm{i}}(t)$, evaluate each objective functions' value $f_k(\boldsymbol{X}_{\mathrm{i}}(t)), k=1,2,\cdots,K$, which represent the objectives such as user satisfaction, network throughput, network load, etc. Update the elite set according to the rules mentioned in section 3.1.

Step 3: If particle i's current position $\boldsymbol{X}_{\mathrm{i}}(t)$ dominates its historical optimal position $\boldsymbol{PBest}_{\mathrm{i}}$, then update $\boldsymbol{X}_{\mathrm{i}}(t)$ as $\boldsymbol{PBest}_{\mathrm{i}}$; select a particle in the elite set as the global optimal solution $\boldsymbol{GBest}$ by using the grid roulette selecting method.

step 4: Updated the particle's speed and position according to formulas (8), (5) and (6) proposed above and set $t=t+1$;

Step 5: Repeat *step 2* to *step 4* until it meets the termination conditions of the algorithm. Select the particle whose objective functions is much more average in the elite set and take it as the final optimal solution. In fact, it is the desired access matrix $\boldsymbol{X}^*$. Select a network to access according to the desired access matrix $\boldsymbol{X}^*$.

3.3 Computational Complexity of MOFPDO Algorithm

We first consider the number of operations for MOFPDO algorithm in one iteration process. Suppose that the size of the population is I, the number of the objective functions is K, and the number of the access matrix's elements is $M \times N$. For each iteration of the particle i, it needs K times to calculate the objective functions and MN times to update the particle's speed and position, so its computational complexity is $O(I \cdot \max\{K, MN\})$. In the actual situation, the number of objective functions tends to be far less than the number of access users, so the complexity becomes $O(IMN)$. Since we decrease rapidly the number of particles that are affected by the mutation operator and the particle swarm optimization converges fast, the number of iterations may not be large. So the entire computational complexity will still be $O(IMN)$, which is perfectly acceptable.

4. Simulation Results and Analysis

Consider a heterogeneous network constituted by two access networks, TD-LTE and WiMAX 802.16e, in which the radius of TD-LTE 's coverage area is 1 km and the radius of WiMAX 's coverage area is 2km. At the beginning of simulations, users distribute in the area covered by either access network uniformly. Users move at the speed of 10m/s. Meanwhile, they update their speed and change the direction of movement at a probability of 0.2 randomly once every 10s. We suppose that handover occurs when users move to the border of a cell. Furthermore, the wireless channel fading model is adopted which is presented in reference [18][19]. Relevant simulation parameters are shown in **Table 1**.

Table 1. Simulation parameters

Parameters	TD-LTE	WiMAX
Number of cells	7	7
Carrier frequency /Bandwidth	2.0GHz/10MHz	3.5GHz/10MHz
Multiple access method	OFDMA	OFDMA
Transmit power of a base station	46dBm	36dBm
Noise power	-170dBm/Hz	-174dBm/Hz
Threshold of User satisfaction degree	1.24Mbit/s	1.24Mbit/s

We take the objectives as load balancing and maximizing users' satisfaction. The load balancing objective function is:

$$\max f_1(x) = \max \sum_{n=1}^{N} \frac{N_{total,m} - N_{load,m}}{N_{n,m}} \tag{9}$$

$$N_{load,m} = \sum_{n=1}^{N_m} N_{n,m} = \sum_{n=1}^{N_m} \frac{1}{1-p_{n,m}} \cdot r_{n,m} \tag{10}$$

When user n accesses network m, $r_{n,m}$ is the two dimensional resource[20][21] that the user need, and $p_{n,m}$ is the packet loss rate; $N_{n,m}$ is the two dimensional resource that the user has actually consumed, and N_m is the number of users that access network m; $N_{load,m}$ is the estimated load in network m, and $N_{total,m}$ is the total number of resources of network m.

Users' satisfaction function is defined as:

$$f_2(x) = N_s / N \tag{11}$$

In fomula (11), N_S is the number of users whose average service rates are greater than the threshold, and N is the number of users that access the network.

In the simulation process, MODPSO algorithm is compared with Load Balancing-based algorithm (LB), User Satisfaction Maximizing-based algorithm (SM) and random access algorithm. Load Balancing-based algorithm will always select the access network with the lightest load currently for a user to minimize the blocking probability, while User Satisfaction Maximizing-based algorithm will always select the access network with maximum transmission rate. The random access algorithm will select an access network randomly.

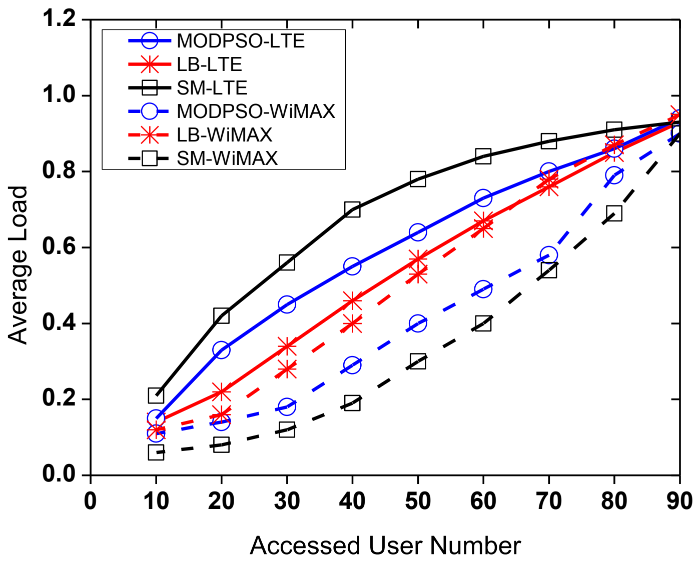

Fig. 4. Average load vs. different accessed user number

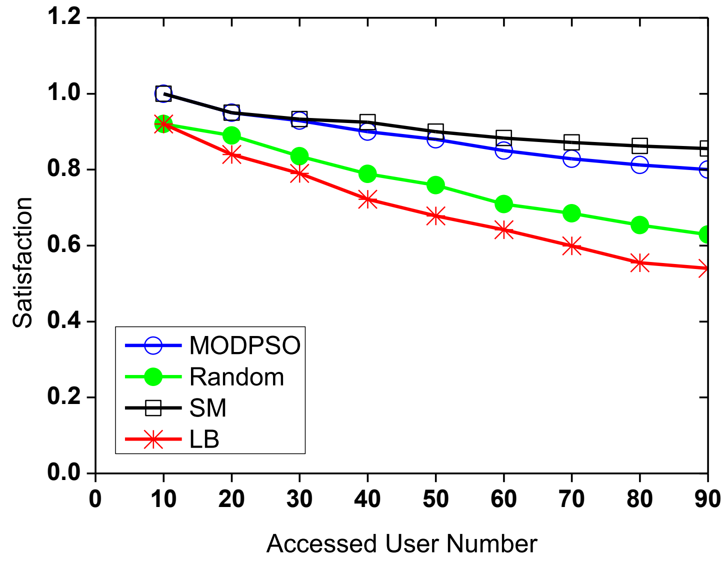

Fig. 5. User's satisfaction degree vs. different accessed user number

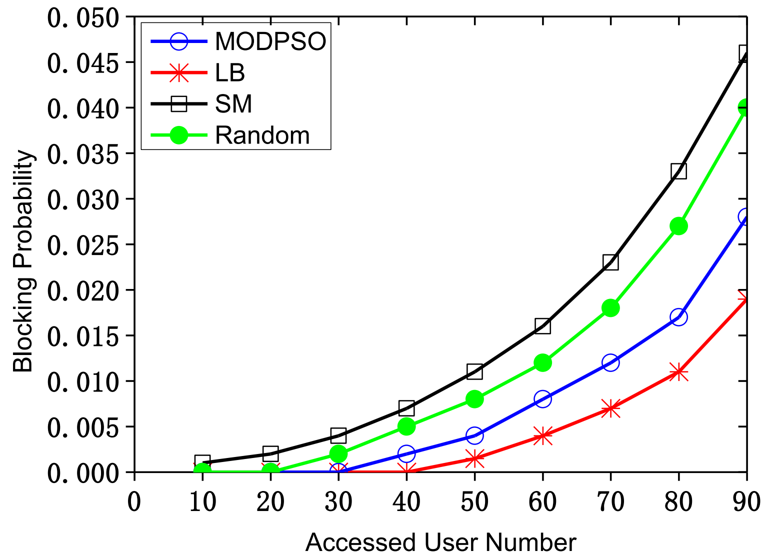

Fig. 6. Blocking probability vs. different accessed user number

In **Fig. 4**, **Fig. 5** and **Fig. 6**, we respectively compare the average load, blocking probability and users' satisfaction of each algorithm with different number of users who locate in the overlapping coverage of the two networks. It can be seen from the simulation results that LB algorithm gains the lowest blocking probability and the two networks' load are more balanced when adopting LB algorithm. However, LB algorithm does not consider a user's QoS requirements, so it shows worse users' satisfaction. For example, its users' satisfaction degree is as low as 55% when the network load is heavy. On the contrary, SM algorithm gets the best users' satisfaction with the worst blocking probability. It makes TD-LTE network's load so heavy that the user can't access TD-LTE network. In contrast, MODPSO algorithm gets the trade-off between blocking probability and users' satisfaction. It can not only make a user's transmission degree to reach a higher level, but also make an access network avoid overload, which may cause serious blocking probability. The algorithm's performance is far superior to the random access algorithm in any aspects that we consider.

5. Conclusion

In this paper a network selection algorithm named MODPSO is proposed, which is used for guiding users to select the most optimal access network in heterogeneous wireless networks. Different to the previous network selection algorithms based on single-objective decision, the MODPSO algorithm considers multiple accessing objectives comprehensively and can achieve multi-objective decision-making. In addition, it abandons the method of changing the targets' weights artificially which is the primary approach used by previous algorithms, so it avoids artificially subjective effects and improves the adaptability to the changing network environment. Simulation results show that compared to the single-objective algorithm, the proposed algorithm can obtain the optimal combination performance and take into account both the network states and the user preferences.

References

[1] L. Zhou, H. Wang, S. Lian, Y. Zhang and A. Vasilakos, "Availability-aware multimedia scheduling in heterogeneous wireless networks," *IEEE Transactions on Vehicular Technology*, vol.60, no.3, pp.1161-1170, Mar. 2011. Article (CrossRef Link)

[2] X. Gelabert, J. Perez-Romero, O. Sallent and R. Agusti, "A Markovian Approach to Radio Access Technology Selection in Heterogeneous Multiaccess/Multiservice Wireless Networks," *IEEE Transactions on Mobile Computing*, vol.7, no.10, pp.1257-1270, Oct. 2008. Article (CrossRef Link)

[3] Y. Zhang, R. Yu, S. Xie, W. Yao, Y. Xiao and M. Guizani, "Home M2M Networks: Architectures, Standards, and QoS Improvement," *IEEE Communications Magazine, special issue on "Recent Progress in Machine-to-Machine Communications"*, vol.49, no.4, pp.44-52, Apr. 2011. Article (CrossRef Link)

[4] Y. J. Kwon and D. H. Cho , "Load Based Cell Selection Algorithm for Faulted Handover in Indoor Femtocell Network," in *Proc. of 2011 IEEE 73rd Vehicular Technology Conference*, pp.1-5, May 15-18, 2011. Article (CrossRef Link)

[5] N. Li and J. Lin, "A two phase RAT selection strategy based on network load and SIR for CDMA-OFDMA heterogeneous networks," in *Proc. of 2010 2nd IEEE International Conference on Network Infrastructure and Digital Content*, pp.90-94, Sept. 24-26, 2010. Article (CrossRef Link)

[6] N. Funabiki, J. Shimizu, T. Nakanishi, K. Watanabe and S. Tomisato, "An Extension of Active Access-Point Selection Algorithm for Throughput Maximization in Wireless Mesh Networks," in *Proc. of 2011 Third International Conference on Intelligent Networking and Collaborative Systems*, pp. 367-372, Nov. 30-Dec. 2, 2011. Article (CrossRef Link)

[7] D. Niyato and E. Hossain, "Dynamics of Network Selection in Heterogeneous Wireless Networks: An Evolutionary Game Approach," *IEEE Transactions on Vehicular Technology*, vol.58, no.4, pp.2008-2017, May, 2009. Article (CrossRef Link)

[8] H. Tabrizi, G. Farhadi and J. Cioffi, "A Learning-Based Network Selection Method in Heterogeneous Wireless Systems," in *Proc. of 2011 IEEE Global Telecommunications*

Conference, pp.1-5, Dec. 5-9, 2011. Article (CrossRef Link)

[9] T. Al-Gizawi, K. Peppas, D. I. Axiotis, E. N. Protonotarios and F. Lazarakis, "Interoperability criteria, mechanisms, and evaluation of system performance for transparently interoperating WLAN and UMTS-HSDPA networks," *IEEE Network*, vol.19, no.4, pp.66-72, July/August, 2005. Article (CrossRef Link)

[10] F. Bari, and V. Leung, "Application of ELECTRE to Network Selection in A Heterogeneous Wireless Network Environment," in *Proc. of IEEE Wireless Communications and Networking Conference*, pp.3810-3815, Mar. 11-15, 2007. Article (CrossRef Link)

[11] O. E. Falowo and O. Olowole, "Effect of RAT selection based on service symmetry and network duplex mode in heterogeneous wireless networks," in *Proc. of IEEE Africon 2011 Conference*, pp.1-6, Sept. 13-15, 2011. Article (CrossRef Link)

[12] W. Sun and Y. Yuan, *Optimization Theory and Methods: Nonlinear Programming*, Springer, New York, 2006.

[13] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proc. of IEEE International Conference on Neural Networks, 1995 Proceedings*, pp.1942-1948 vol.4, Nov. 27-Dec.1, 1995. Article (CrossRef Link)

[14] J. Kennedy and R. Mendes, "Neighborhood topologies in fully informed and best-of-neighborhood particle swarms," *IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews*, vol.36, no.4, pp.515-519, July, 2006. Article (CrossRef Link)

[15] A. P. Engelbrecht, *Fundamentals of Computational Swarm Intelligence*, Wiley, Hoboken, NJ, 2005.

[16] C. A. C. Coello, G. T. Pulido and M. S. Lechuga, "Handling multiple objectives with particle swarm optimization," *IEEE Transactions on Evolutionary Computation*, vol.8, no.3, pp.256-279, Jun., 2004. Article (CrossRef Link)

[17] X. L. Long, "Network-based Multi-robot System Research," *PhD dissertation*, Zhejiang University, 2007. Article (CrossRef Link)

[18] IEEE Std 802.16^{TM}-2009, "Part 16: Air Interface for Broadband Wireless Access Systems," May, 2009. Article (CrossRef Link)

[19] M. Hempel, H. Sharif, W. Wang, T. Zhou and P. Mahasukhon, "A Study of Critical Baseline Performance Characteristics for IEEE 802.16e-2005," in *Proc. of International Wireless Communications and Mobile Computing Conference*, 2008, pp.837-842, Aug. 6-8, 2008. Article (CrossRef Link)

[20] G. Bianchi and I. Tinnirello, "Improving load balancing mechanisms in wireless packet networks," in *Proc. of IEEE International Conference on Communications*, 2002, pp.891-895 vol.2, Apr. 28-May 2, 2002. Article (CrossRef Link)

[21] C. Y. Wong and R. S. Cheng, "Multiuser OFDM with adaptive subcarrier, bit and power allocation," *IEEE Journal on Selected Areas in Communications*, vol.17, no.10, pp.1747-1758, Oct. 1999. Article (CrossRef Link)

Wenzhu Zhang received the B.S., M.S., and Ph.D. degrees in communications engineering from Xidian University, Xi'an, China, in 1994, 1999, and 2004, respectively. From 2005 to 2006, he was a research associate at Illinois Institute of Technology, Chicago, Illinois, where he was responsible for the development in research of new radio access technology. From 2012 to 2013, he was a postdoctoral researcher with Inha University, Incheon, Korea. He is currently an associate professor in the School of Telecommunications Engineering, Xidian University. His research interests include the field of ad hoc wireless network protocol designing, network performance analyzing, and cognitive radio network.

Kyung S. Kwak received the B.S. degree from the Inha University, Incheon, Korea in 1977, and the M.S. degree from the University of Southern California in 1981 and the Ph.D degree from the University of California at San Diego in 1988, under the Inha University Fellowship and the Korea Electric Association Abroad Scholarship Grants, respectively. From 1988 to 1989 he was a Member of Technical Staff at Hughes Network Systems, San Diego, California. From 1989 to 1990 he was with the IBM Network Analysis Center at Research Triangle Park, North Carolina. Since then he has been with the School of Information and Communication, Inha University, Korea as a professor. He had been the chairman of the School of Electrical and Computer Engineering from 1999 to 2000 and the dean of the Graduate School of Information Technology and Telecommunications from 2001 to 2002 at the Inha University, Incheon, Korea. He is the current UWB Wireless Communications Research Center, a key government IT research center, Korea. He is now Inha Fellow Professor (IFP). Since 1994 he had been serving as a member of Board of Directors, and he had been the vice president for Korean Institute of Communication Sciences (KICS) during the term of 2002-2000 year. He was the KISC's president of 2006 year term. In 1993, he received Engineering College Young Investigator Achievement Award from Inha University, and a distinguished service medal from the Institute of Electronics Engineers of Korea (IEEK). In 1996 and 1999, he received Distinguished Service Medals from the KICS. He received the Inha University Engineering Paper Award and the LG Paper Award in 1998, and Motorola Paper Award in 2000. His research interests include multiple access communication systems, mobile communication systems, UWB radio systems and ad-hoc networks, high-performance wireless Internet. Mr. Kwak is members of IEEE, IEICE, KICS and KIEE.

Chengxiao Feng received his B.S degree of communication and information system from Xidian University, Xi'an, China, in 2010. He is currently a Master degree candidate in the School of Telecommunications Engineering, Xidian University. His research interests include the field of ad hoc networks and cognitive radio network.