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A Monte Carlo Enhanced PSO Algorithm for Optimal QoM in Multi-Channel Wireless Networks

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Abstract In wireless monitoring networks, wireless sniffers are distributed in a region to monitor the activities of users. It can be used for fault diagnosis, resource management and critical path analysis. Due to hardware limitations, wireless sniffers typically can only collect information on one channel at a time. Therefore, it is a key topic to optimize the channel selection for sniffers to maximize the information collected, so as to maximize the quality of monitoring (QoM) of the network. In this paper, a particle swarm optimization (PSO)-based solution is proposed to achieve the optimal channel selection. A 2D mapping particle coding and its moving scheme are devised. Monte Carlo method is incorporated to revise the solution and significantly improve the convergence of the algorithm. The extensive simulations demonstrate that the Monte Carlo enhanced PSO (MC-PSO) algorithm outperforms the related algorithms evidently with higher monitoring quality, lower computation complexity, and faster convergence. The practical experiment also shows the feasibility of this algorithm.

Keywords multi-channel wireless network, channel selection, quality of monitoring, Monte Carlo, particle swarm optimization

1 Introduction

With the growing applications of wireless networks (e.g., WLAN, WiFi, WiMax, Mesh), high quality management of wireless users and networks is becoming more and more important[1−3]. It has been a key point to monitor the network status and performance accurately and in real time, so as to implement the effective management.

In wireless monitoring networks, special monitoring equipments are used to collect the information transmitted by wireless users in the monitoring area, and the frame or physical layer information (PHY) is saved for distributed or centralized analysis. Wireless monitoring is usually realized using Simple Network Management Protocol (SNMP) and base station logs. Since they reveal the detailed PHY (e.g., signal strength and spectrum density) and MAC behaviors (e.g., collision and retransmission), as well as timing information, they are essential for network diagnosis and management.

The wireless monitoring equipment (sniffer) is usually a single-radio multi-channel device[4-5]. That is to say, it has multi optional channels①. So, it is a key topic to allocate channels and other resources for sniffers to optimize the monitoring quality of the entire network. In literature [6], it has turned out to be an NP-hard problem in user-center mode, and an effective solution for the problem will be with great significance to the performance improvement of all kinds of wireless application networks.

In the paper, we investigate the channel allocation of the sniffers and propose an optimization algorithm for the problem. The rest of paper is organized as follows. In Section 2, we provide a brief review of the existing multi-channel techniques about wireless networks. The channel selection problem is formulated in Section 3. The Monte Carlo Enhanced Particle Swarm Optimization algorithm (MC-PSO) is detailed in Section 4

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①In IEEE 802.11.b/g WLAN, there are three orthogonal channels, and in IEEE 802.11.a WLAN, there are 12 orthogonal channels.

followed by simulation experiments in Section 5. Finally, we conclude this paper with some future work in Section 6.

2 Related Work

Existing multi-channel researches about wireless networks fall into two categories: the multi-channel allocation of wireless network itself and the multi-channel selection for wireless monitoring network. The mentioned two kinds of networks are shown in Fig.1.

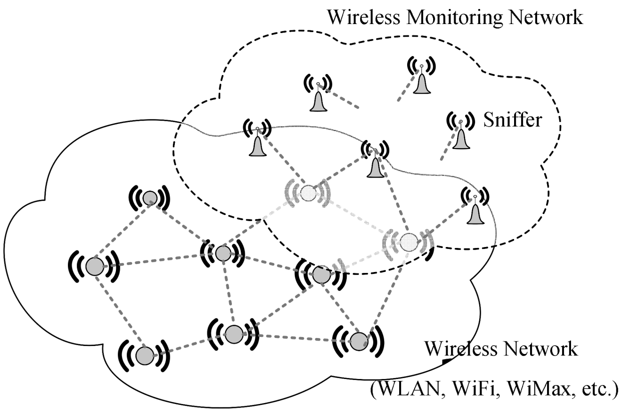

Fig.1. Wireless network and wireless monitoring network.

2.1 Multi-Channel Allocation of Wireless Network Itself

As the extension of cable network, wireless network technology develops rapidly, and has been widely applied in many industry and living fields. In these applications, to eliminate the collision and interference, and improve the communication capability, the multi-channel technology has been introduced in wireless network successfully. According to the different numbers of the interfaces, the multi-channel technology includes "single-radio multi-channel" and "multi-radio multi-channel". For the consideration of cost and efficiency, the number of radios is less than that of channels. Therefore, it has been a research emphasis to allocate the channels for radios to achieve the optimal package transmission efficiency.

From [7-14], we can get an overview of much excellent work in multi-channel allocation of wireless network. In 2000, Wu *et al.*[7] proposed an on-demand Dynamic Channel Assignment protocol (DCA). Each host maintains one dedicated channel for control messages and other channels for data. In this protocol, the multi-channel hidden terminal problem does not occur, and the time synchronization is released. But when the number of channels is small, one channel dedicated for control messages will be costly. In 2004, Bahl *et al.*[8] presented a link-layer protocol called Slotted Seeded Channel Hopping (SSCH). Two nodes use a pseudo-random sequence, driven by a set of seeds, to decide which channel to switch. It does not need dedicated channel for control, which improves channel utilization. But it needs synchronization, which is difficult to achieve. In 2004, So *et al.*[9] proposed a MAC solution for multi-channel (MMAC). In the solution, time is divided into beacon intervals. At the start of each interval, every node uses prefer channel list (PCL) to negotiate with the channel for data communication. It greatly improves the efficiency of the data transmission, but requires tight synchronization. In addition, the switching of intervals will affect the efficiency of the system. In 2010, Hou *et al.*[10] studied the channel selection problem in cognitive radio networks, described it as a binary integer nonlinear optimization problem, and proposed an algorithm based on priority order to maximize the total channel utilization for all secondary nodes. In 2011, an interface-clustered channel assignment (ICCA) scheme was presented by Du *et al.*[11] It can eliminate the collision and interference to some extent, enhance the network throughput, and reduce the transmission delay. In 2012, Chaudhry *et al.*[12] proposed a Topology-Controlled Interference-Aware Channel-Assignment algorithm (TICA). This algorithm uses topology control to assign channels for multi-radio mesh routers, so that the interference is reduced, the network throughput is improved, and the connectivity is guaranteed.

2.2 Multi-Channel Selection for Wireless Monitoring Network

In recent years, wireless networks monitoring has become a hot topic. The research mainly contains monitoring device, system design, fault diagnosis, etc.[15-20] In 2004, "passive monitoring" based on multi wireless sniffers was first introduced by Yeo *et al.*[15-16] They analyzed the advantages and challenges of wireless passive monitoring, and preliminarily set up an application system, which fulfills the network fault diagnosis based on the time synchronization and data fusion of the multi sniffers. In 2005, Rodrig *et al.*[17] used sniffers to capture wireless communication data and analyze the performance characteristics of 802.11 WiFi network. In 2006, Cheng *et al.*[18] investigated a large-scale monitoring network composed of 150 sniffers, and discussed the time synchronization method for the distributed sniffers. In 2007, Yang *et al.*[19] studied the lifetime model of wireless monitoring networks, and proposed to adjust the sensing and communication radius of sniffers in real time to maximize the lifetime of networks. In 2010, Liu *et al.*[20] investigated the relationship between the number of monitoring sniffers and false alarm rate, and put forward an algorithm based on poller-pollee structure, which can limit the false alarm rate and minimize the number of sniffers.

Due to the multi-channel characteristic of the wireless network (monitored object), the wireless monitoring network must be equipped with the same channel resource. Consequently, it has become an important subject to optimize the channel selection of the sniffers to improve the performance of the wireless monitoring network. In 2009, Shin *et al.*[21] studied the channel selection of sniffers in wireless Mesh network to maximize the coverage of users. They described it as a maximum coverage problem based on group budget constraints[22-23], and solved it using Greedy and Linear Programming (LP) algorithms, which achieved good performance. Based on the researches above, Chhetri *et al.*[6] formulated the problem of channel selection of sniffers, and proved it to be NP-hard to maximize the quality of monitoring (QoM) of the network under the universal network model. Greedy and LP algorithms were employed to solve the problem. Greedy algorithm always seeks the solution with maximal current benefit during the process of resolution, and misses the global optimal solution or the approximate of it. Although LP algorithm can achieve better solution than others, its complexity is too high to meet the real-time requirement in the dynamic wireless networks. In 2011, we applied Gibbs sampler theory to address the problem, and proposed a distributed channel selection algorithm for sniffers to maximize the QoM of the wireless monitoring network[24]. This method utilizes the local information to select the channel with low Gibbs energy, but cannot achieve the global optima in most cases.

In this paper, we introduce particle swarm optimization (PSO) for the channel selection of sniffers to maximize the QoM of the wireless monitoring networks. Monte Carlo method is incorporated to revise and optimize the solution. Extensive simulations and practical experiments demonstrate that the proposed algorithm outperforms other algorithms not only in the quality of solution, but also in efficiency.

3 Problem Description

3.1 Network Model

Consider a wireless monitoring network with m monitoring sniffers, n users, and k optional channels. $S = \{s_1, s_2, \ldots, s_m\}$ is the set of sniffers, $U = \{u_1, u_2, \ldots, u_n\}$ is the set of users, and $C = \{c_1, c_2, \ldots, c_k\}$ is the set of channels. In homogeneous network, sniffers have the same transmission characteristics. They can read the frame information and analyze the information from users or other sniffers, but they can only work on one channel at a time. During a period of time, user u_j ($j = 1, 2, \ldots, n$) works on channel $c(u_j) \in C$, and transmits data with probability p_{u_j}. These users can be wireless routers, access points or mobile phones, etc. If a user sends data through a channel at time t, it will be called an "active user" at time t.

In wireless monitoring network, the relationship between sniffers and users can be described by an undirected bi-partite graph $G = (S, U, E)$ shown in Fig.2. If u_j is in the monitoring area of s_i, there will be an edge between them, denoted by $e = (s_i, u_j)$. When s_i and u_j work on the same channel, s_i can capture the data from u_j , then we say u_j is covered by s_i. E represents the set of all connecting edges. If a user is outside of all sniffers' monitoring area, it is excluded from G. The vertex v of G is a sniffer or user, namely $v \in S \cup U$. $N(v)$ denotes the neighbors of vertex v. If the vertex is a sniffer s_i, $N(s_i)$ is the set of neighbor users of s_i; if the vertex is a user u_j, $N(u_j)$ means its neighbor sniffers. If a sniffer is inside of the communication range of another sniffer, they are called adjacent sniffers. $W(s_i)$ denotes the set of adjacent sniffers of s_i, and B_{s_i} is the set of subscript of sniffers in $W(s_i)$. In this paper, we assume that the communication radius of sniffer is twice as its monitoring radius.

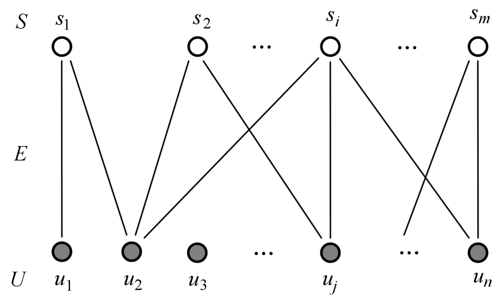

Fig.2. Undirected bi-partite graph G.

3.2 Problem Formulation

Let $\boldsymbol{a}$: $S \to C$ represent a channel selection scheme for wireless monitoring networks, and A is the set of all possible schemes. Scheme $\boldsymbol{a}$ can be expressed in the form of vector as follows: $\boldsymbol{a} = (a(s_1), a(s_2), \ldots, a(s_m))$, where $a(s_i) \in C$ is the channel selected by s_i. When s_i selects the channel $a(s_i)$, it can communicate with the neighbor users, who also work on $a(s_i)$. Given a channel selection scheme $\boldsymbol{a}$, then $S = \cup_{q=1}^{k} S_{c_q}$, $U = \cup_{q=1}^{k} U_{c_q}$, where S_{c_q} denotes the set of sniffers assigned to channel c_q, and U_{c_q} denotes the set of users working on channel c_q. Now it is able to show the relationship between all the sniffers and users working on channel c_q in the form of undirected bi-partite graph $G_{c_q} = (S_{c_q}, U_{c_q}, E_{c_q})$.

Definition 1 (Quality of Monitoring of Sniffer (QoM-S)). *When wireless monitoring network works on channel $\boldsymbol{a} \in A$, the quality of monitoring of sniffer s_i can be defined as follows*:

$$Q_{s_i}(\boldsymbol{a}) = \sum_{u \in N(s_i)} p_u \times \frac{\mathbf{1}(c(u) = a(s_i))}{\mathbf{1} + \sum_{t \in B_{s_i}} \mathbf{1}(c(u) = a(s_t), s_t \in N(u))},$$

where $\mathbf{1}(\cdot)$ is an indicator function. It equals 1 when the condition is true, and 0 otherwise. It is clear that the more neighbor users working on the same channel as s_i, and the higher transmission probability these users have, meanwhile, the less other sniffers covering these users, the higher monitoring quality s_i has. QoM-S reflects the number of active users available to s_i under the channel selection scheme $\boldsymbol{a}$. Active users are in the state of sending data.

Definition 2 (Quality of Monitoring of Network (QoM-N)). *Given a channel selection scheme $\boldsymbol{a}$, the quality of monitoring of the wireless monitoring network can be defined as follows*:

$$Q(\boldsymbol{a}) = \sum_{s_i \in S} Q_{s_i}(\boldsymbol{a}). \quad (1)$$

So, the higher QoM-N is, the more active users can be monitored in the network, and the higher quality of service the wireless monitoring network provides.

The problem of maximizing QoM-N can be described as follows: with limited users and sniffers in a wireless monitoring network, to search for a channel selection scheme for sniffers to maximize the QoM of the wireless monitoring network, so that the sniffers will collect the maximal information transmitted by active users.

The channel selection scheme will be changed according to probability during different time slots. So the maximal information collected by the monitoring network in a certain period can be expressed as:

$$\begin{aligned} &\max \sum_{\boldsymbol{a} \in A} Q(\boldsymbol{a}) \times \pi(\boldsymbol{a}) \\ &\text{s.t.} \quad \pi(\boldsymbol{a}) \in [0, 1], \quad \sum_{\boldsymbol{a} \in A} \pi(\boldsymbol{a}) = 1, \end{aligned} \quad (2)$$

where, $\pi(\boldsymbol{a})$ is the probability for the wireless monitoring network to work on the channel scheme $\boldsymbol{a}$.

From (2), the optimal channel selection scheme is as follows:

$$\boldsymbol{a}^* = \arg\max Q(\boldsymbol{a}). \quad (3)$$

We introduce PSO to solve this complicated combination optimization problem.

4 Channel Selection Algorithm

4.1 Particle Swarm Optimization

PSO is a population-based stochastic optimization technique developed by Eberhart and Kennedy[25-26], inspired by the social behavior of bird flocking and fish schooling. PSO shares many similarities with evolutionary computation techniques. The system is initialized with a population of random solutions and searches for the optima by updating generations.

In PSO, the potential solutions are called particles. All the particles have fitness values which are evaluated by the fitness function to be optimized, and have the velocities which direct the moving of the particles. The particles fly through the problem space by following the current optimum particles.

PSO is initialized with a group of random particles (solutions) and then searches for the optima by updating generations. In every iteration, each particle is updated by following two "best" values. One is the best solution that has been achieved so far (its fitness value is stored). This value is called "pbest". The other "best" value tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called "gbest".

In the past several years, PSO and DPSO (Discrete Particle Swarm Optimization)[27-29] have been successfully applied in many research and application areas. It is demonstrated that they can get better results in a faster and cheaper way, and with fewer parameters to adjust than most other methods.

The key technique to solve the practical problems by using DPSO is to seek the suitable coding expression of particle for the problem space as well as the fitness function. The problem-specific domain knowledge and constraints should be incorporated into the algorithm to obtain the optimal solution and improve the convergence rate of the algorithm.

4.2 2D Mapping Particle Encoding

In this subsection, we introduce a novel particle coding for the channels selection resolution, termed "2D mapping particle coding". As illustrated in Fig.3, each particle is a two-dimension (2D) binary matrix $\boldsymbol{O} = (o_{ij})_{k \times m}$. It corresponds to the searching space of the channels selection problem as shown in Fig.4. $o_{ij} = 1$ expresses the j-th sniffer working on channel c_i. Because the number of elements "1" in a column should be 1, we have the following constraint, which need to be satisfied through the particle moving:

Column Singularity: the number of "1" in each column of legitimate particle should be 1.

The coding method of 2D mapping particle is advantageous over other types of encoding because it is suitable for the 2D attribute of the channels selection problem. As will be demonstrated in later subsection, it facilitates great flexibility in incorporating domain knowledge to the algorithm.

	$j=1$	2	...	m
$i=1$	0	0	...	**1**
2	**1**	0	...	0
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$k-1$	0	**1**	...	0
k	0	0	...	0

Fig.3. Particle coding.

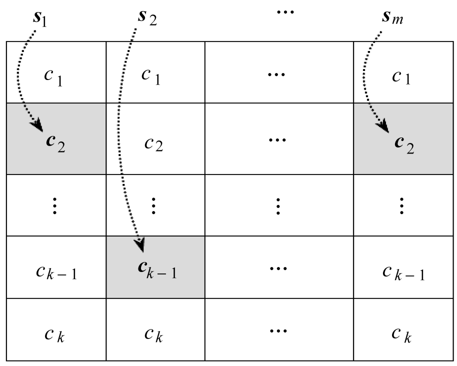

Fig.4. Searching space of the channel selection problem.

4.3 Initialization of Particles

Randomly generate $k \times m$ binary numbers, which construct a 2D particle coding $\boldsymbol{O} = (o_{ij})_{k\times m}$. However, this particle coding may violate the column singularity. In fact, the number of elements "1" in the columns may be larger or smaller than 1 as shown in Fig.5(a). To satisfy the singularity, we revise the initial particles by the following steps:

Given the particle $\boldsymbol{O}$, with the elements o_{ij}:

Step 1. Randomly choose one column j from $\boldsymbol{O}$ which is not processed. If the number of elements "1" in this column is 1, transfer to step 4;

Step 2. If $\sum_{i=1}^{k} o_{ij} > 1$, execute Monte Carlo optimized selection:

for each i ($o_{ij} = 1$), compute:

$$Q_{s_j}(i) = \sum_{u\in N(s_j)} p_u \cdot \mathbf{1}(c(u) = c_i),$$

$$\varepsilon(i) = \max_{o_{ij}=1}\{Q_{s_j}(i)\} - Q_{s_j}(i),$$

$$\pi_T(i) = \frac{1}{Z_T} e^{-\frac{1}{T}\varepsilon(i)},$$

where, $T > 0$ denotes the temperature, energy function $\varepsilon(i)$ represents the energy of channel i, $0 < \varepsilon(i) < +\infty$. $Z_T = \sum_{o_{ij}=1} e^{-\frac{1}{T}\varepsilon(i)}$, then $\pi_T(i) \in [0, 1]$. Then select a bit to be 1 using roulette rule according to the probability $\pi_T(i)$ (Fig.5(b));

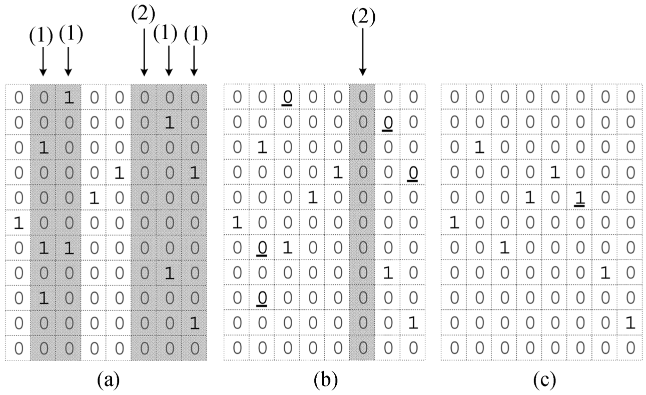

Fig.5. Revision of initial particle. (1) represents the number of elements "1" in the columns is larger than 1; (2) represents the number is zero. (a) Illegitimate particle. (b) Partially revised particle. (c) Legitimate particle. The bits underlined are the bits that have been removed or added.

Step 3. If $\sum_{i=1}^{k} o_{ij} = 0$, compute $\pi_T(i) = \frac{1}{Z_T} e^{-\frac{1}{T}\varepsilon(i)}$, $i = 1, \ldots, k$, and select a bit to be 1 using roulette rule according to $\pi_T(i)$ (Fig.5(c));

Step 4. Repeat step 1, until $\sum_{i=1}^{k} o_{ij} = 1$ ($j = 1, \ldots, m$).

Monte Carlo method is a class of computational algorithm that relies on repeated random sampling to compute the probability result. It is very suitable to be used when it is infeasible to compute an exact result using a deterministic algorithm. Furthermore, it has been proved that while the iteration number $t \to \infty$, the algorithm will converge to the state with the global lowest energy, which is the optimal solution[30-31].

In step 2, the redundant elements "1" are removed to construct a legitimate particle. Instead of randomly deciding which one to be removed, we find the element o_{*j} that can maximize the monitoring quality of sniffer s_j, reserve it, and remove the other elements "1", because o_{*j} is most likely to be better than other solutions. In step 3, an element "1" is added in the column. We compute the election probability of each bit in this column, and decide which one to be "1" according to the probability. A bit which can maximize the monitoring quality of sniffer s_j will have more chance to be elected. This revision process incorporates domain knowledge to form better initial particles than the random method.

By the end of the procedure, a legitimate initial particle is generated satisfying the column singularity.

In this manner, multi particle codings are generated as the initial swarm.

4.4 Moving of Particles

In each iteration, all the particles move in the searching space to find the global optima. The velocity and position of each particle are updated by the following formulas:

$$v_{id}(t+1) = w \times v_{id}(t) + c_1 \times r_1 \times (P_{id} - x_{id}(t)) + c_2 \times r_2 \times (P_{gd} - x_{id}(t)), \quad (4)$$

$$x_{id}(t+1) = \begin{cases} 1, & \text{if } \rho_{id}(t+1) < \mathit{sigmoid}\,(v_{id}(t+1)), \\ 0, & \text{otherwise}, \end{cases}$$

where the variable i denotes the i-th particle in the swarm, d is the d-th dimensional value of the vector, $1 \leqslant d \leqslant k \times m$, t represents the current iteration number, $\boldsymbol{v}_i$ is the velocity vector of the i-th particle, $\boldsymbol{x}_i$ is the position vector of the i-th particle, P_i is the individual best position that the i-th particle has reached, P_g is the global best position that all the particles have reached, w is called inertia weight, c_1 and c_2 are two parameters which are called cognitive confidence coefficients, r_1 and r_2 are random values between 0 and 1, ρ_i is a quasi-random value selected from a uniform distribution in $[0.0, 1.0]$. $\mathit{sigmoid}(v) = 1/(1+\exp(-v))$. Furthermore, the largest moving velocity is restricted by $v_{\max}$, that is $|\ v_{id}(t+1)\ | \leqslant v_{\max}$, which limits the ultimate probability that bit $x_{id}(t+1)$ will take on a binary value. A smaller $v_{\max}$ will allow a higher mutation rate.

However, the updated particles may also violate the column singularity. The number of elements "1" in the resulting columns may be larger or smaller than 1 as shown in Fig.6(b) and Fig.7(b). To satisfy the singularity, we revise the updated particles using the former

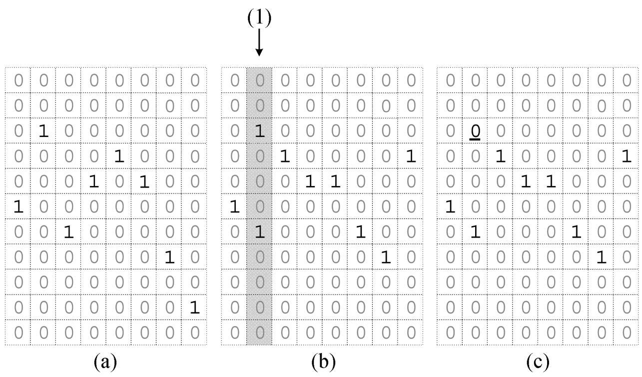

Fig.6. Revision of the updated particle. (a) Former particle. (b) Updated particle. (c) Revised particle.

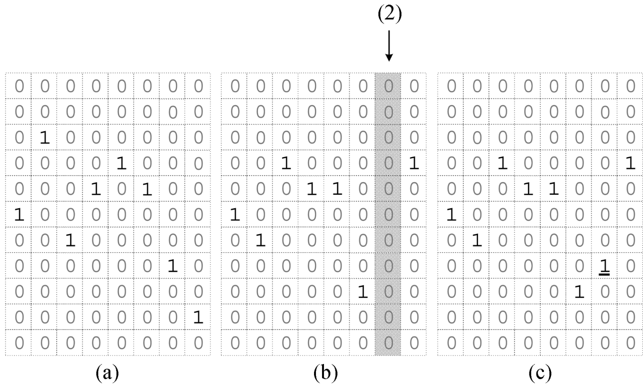

Fig.7. Revision of the updated particle. (a) Former particle. (b) Updated particle. (c) Revised particle.

steps to form legitimate particles as shown in Fig.6(c) and Fig.7(c).

4.5 Adjustment of Inertia Weight and Learning Factors

Suitable selection of inertia weight w, c_1 and c_2 in (4) provides a balance between global and local exploration and exploitation, and results in less iterations required to find a sufficient optimal solution. The inertia weight w can be set according to the following formula:

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{t_{\max}} \times t,$$

where $t_{\max}$ is the maximum iteration number, $w_{\max}$ is the maximum inertia weight, $w_{\min}$ is the minimum inertia weight. So, w decreases linearly during a run.

The learning factors c_1 and c_2 can be adjusted as follows:

$$c_1 = c_{1i} + \frac{c_{1f} - c_{1i}}{t_{\max}} \times t,$$

$$c_2 = c_{2i} + \frac{c_{2f} - c_{2i}}{t_{\max}} \times t,$$

where c_{1i}, c_{1f}, c_{2i}, c_{2f} are the initial values and the final values of c_1 and c_2 separately. Then, c_1 decreases linearly during a run; while c_2 increases linearly at the same time. The asynchronously varying learning factors and inertia weight have been proved to be beneficial to the convergence of the algorithm[27].

4.6 Sketch of Channel Selection Resolution Algorithm

Based on the discussion, we present the Monte Carlo enhanced PSO (MC-PSO) channel selection algorithm as Algorithm 1:

Algorithm 1. MC-PSO Channel Selection Algorithm
Input: Sniffer set $S = \{s_1, s_2, \ldots, s_m\}$,
user set $U = \{u_1, u_2, \ldots, u_n\}$,
$c(u_j)$ and p_{u_j} $(j = 1, 2, \ldots, n)$,
the maximum iteration number $t_{\max}$;
Output: Channel selection vector $\boldsymbol{a}$;
$x_i(t) \leftarrow$ Generate the initial particles, $1 \leqslant i \leqslant N$; $t = 0$;
Set $V_i(t) = 0$;
Revise the initial particles to satisfy singularity;
$Q_i(t) \leftarrow$ *function*$(x_i(t))$;
/* `compute the target function value of each particle according to (1)`*/;
$Q^* = \max(Q_i(t))$; /*`choose the maximum value`*/;
Set the pbest $P_i = x_i(t)$ and $\overline{Q_i} = Q_i(t)$;
Set the gbest $P_g = x_*(t)$ with Q^*;
do
  $x_i(t+1) \leftarrow$ All particles move to new positions;
  Revise the updated particles to satisfy singularity;
  $Q_i(t+1) \leftarrow$ *function*$(x_i(t+1))$;
  if $(Q_i(t+1) > \overline{Q_i})$ **then**
    $P_i = x_i(t+1)$; /*`update the pbest`*/;
    $\overline{Q_i} = Q_i(t+1)$;
  end
  if $(Q_i(t+1) > Q^*)$ **then**
    $P_g = x_i(t+1)$; /* `update the gbest` */;
    $Q^* = Q_i(t+1)$;
  end
  $t = t + 1$;
While $(t > t_{\max})$;

5 Experimental Results

5.1 Simulations

In this section, we evaluate the performance of MC-PSO algorithm, comparing with three baseline algorithms:

Greedy: select channel for each sniffer to maximize the sum of transmission probability of its neighbor users.

Linear Programming (*LP*): solve the integer programming problem from (3).

Gibbs Sampler: a sniffer computes the local energy of the optional channels and their selection probability, then chooses one channel according to the probability.

In this paper, we conduct extensive comparing experiments. The program is run on a PC with Intel® Core™2 CPU @2.40 GHz, 2 GB memory. The software platform is Windows XP.

We conduct three sets of experiments, and the number of the optional channels is 3, 6, and 9 respectively. In each experiment, the four algorithms are compared on different aspects of performance. MC-PSO and Gibbs Sampler both run 20 times to get the average result for evaluation. Table 1 lists the parameters of MC-PSO, where N is the number of particles. Large N can promote the searching ability of the algorithm, meanwhile extend the running time of program. The other parameters are all set as the experience values for DPSO applications, and the experiments results also show the validity in this case.

Table 1. Parameters Setting of MC-PSO Simulation

N	$v_{\max}$	$w_{\max}$	$w_{\min}$	c_{1i}	c_{1f}	c_{2i}	c_{2f}	$t_{\max}$
20	6	0.9	0.4	2.5	0.5	0.5	2.5	100

In the first set of experiments, 1 000 users are distributed in $500 \times 500\text{m}^2$ square field as shown in Fig.8, and transmission probability $p_u \in [0, 0.06]$. The field is partitioned in several regular hexagon units to construct the cellular framework. Each unit center is equipped with a base station (BS) working on a certain channel, and users in the unit work on the same channel as BS. Every two adjacent units are on different channels. Twenty-five sniffers are deployed uniformly in the field to form a monitoring network to collect the communication activities of the users in this field. Monitoring radius of sniffer is 120 meters, and the sniffer has 3 optional channels[②].

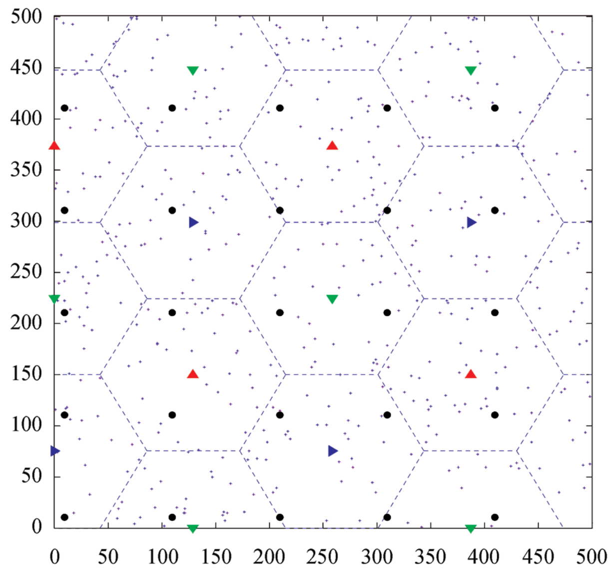

Fig.8. Wireless network topology. Hexagonal layout with users (purple "+"), sniffers (solid dots), and base-stations (isosceles triangles) in each cell (different colors representing working on different channels).

②In IEEE 802.11.b/g WLAN, there are three orthogonal channels, the 1st, 6th, and 11th, with center frequency 2 412 MHz, 2 437 MHz and 2 462 MHz, respectively.

MC-PSO, LP, Greedy, and Gibbs Sampler are applied respectively to solve the channel selection scheme for sniffers. The quality of solution (QoM) of the four algorithms are shown in Fig.9.

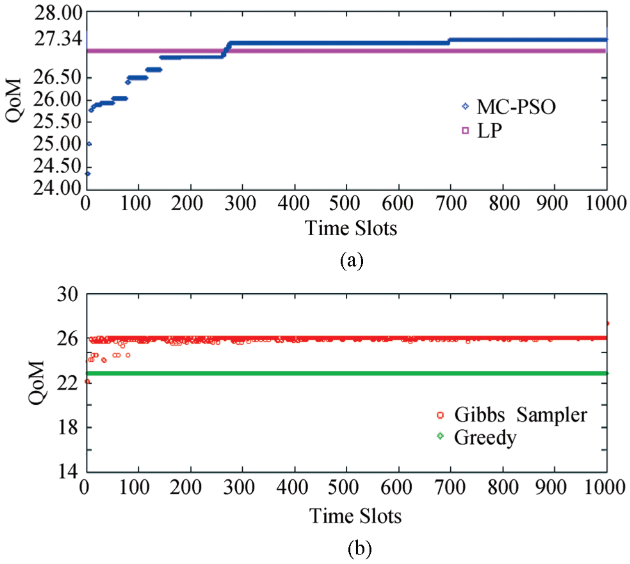

Fig.9. Performance comparison of the four algorithms in the first set of experiments (3 optional channels).

As depicted in Fig.9(a), after 700 iterations, the proposed MC-PSO algorithm converges to the extremely optimal solution (QoM = 27.338). LP algorithm takes the second place with QoM up to 27.105, while Gibbs Sampler and Greedy algorithm achieve the QoM of 26.052 and 22.872 respectively (shown in Fig.9(b)). It is shown that the Monte Carlo based solution revision improves the convergence of PSO algorithm effectively, and enhances its global searching ability.

Table 2 demonstrates the statistical results of the three sets of experiments. Among the four algorithms, MC-PSO and Gibbs Sampler both run 20 times in each set of experiments to get the average optimal solution and their QoM value. As deterministic methods, LP and Greedy just run once. From Table 2, we can see that MC-PSO outperforms LP in three sets of experiments, and is evidently better than Gibbs Sampler and Greedy. Furthermore, MC-PSO converges fast, with shorter running time than Gibbs Sampler.

In this paper, Monte Carlo method is incorporated to revise the solution of algorithm. We conduct the extended experiments to test its effect on the performance of algorithm. We compare the convergence performance of PSO using Monte Carlo revision (MC-PSO) with PSO using random revision (R-PSO). Fig.10 shows the magnitude distribution of MC-PSO and R-PSO. Each row represents the results obtained by different algorithms; each column represents the results obtained in different sets of experiments. The histograms of convergence iteration are plotted with a 50-iteration increment. The histograms can be regarded as an approximation of the probability density function of the convergence iteration. It is shown that, in the first set of experiments, more than 75% convergences are during 500∼700 iterations for MC-PSO algorithm; meanwhile, most of convergences are from 700 to 800 iterations for R-PSO algorithm. The other two sets of experiments present the similar experimental results. (In this paper, the convergence iteration of algorithm is defined as the iteration while the MC-PSO/R-PSO program running achieves better solution than LP, and the solution does not evolve during more than 20 iterations.)

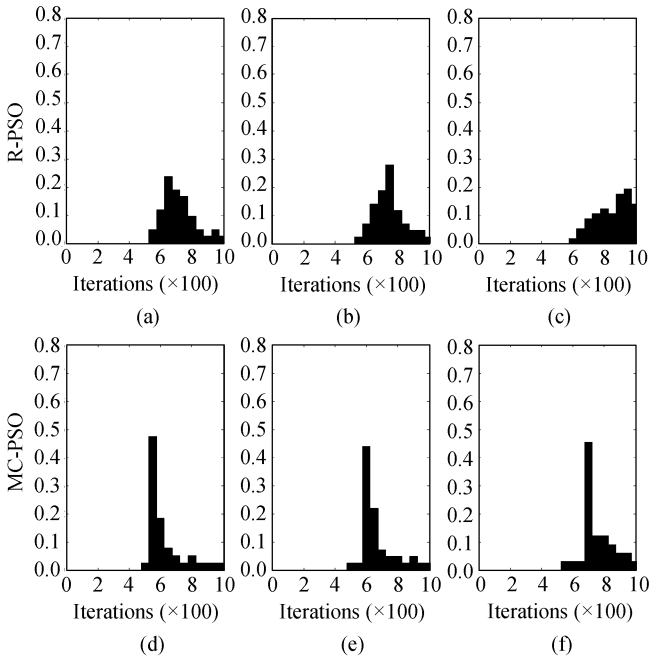

Fig.10. Magnitude distribution of convergence iteration. (a) $k = 3$. (b) $k = 6$. (c) $k = 9$. (d) $k = 3$. (e) $k = 6$. (f) $k = 9$.

Table 2. Statistical Results of Three Sets of Experiments

No. Experiment	MC-PSO		Gibbs Sampler		LP		Greedy	
	Average Optimal QoM	Running time (s) (1 000 Iterations)	Average Optimal QoM	Running time (s) (1 000 Iterations)	QoM	Running time (s)	QoM	Running time (s)
1 (3 channels)	27.338	10.616	26.052	28.938	27.105	0.562	22.872	0.093
2 (6 channels)	26.760	11.695	26.261	30.953	26.484	0.812	23.363	0.109
3 (9 channels)	26.263	11.759	26.140	35.031	26.088	0.934	23.481	0.119

From the experimental results above, we can see that based on Discrete Particle Swarm Optimization theory, utilizing the collaborative searching of the particle swarm in the multi-dimension solution space, the proposed MC-PSO algorithm can achieve the optimal position (the optimal channel selection scheme), so as to maximize the QoM of wireless monitoring network. Monte Carlo method is incorporated to revise the illegitimate particle (solution) to legitimate one during the evolution of particle swarms. This operation significantly improves the quality of solution and the convergence of algorithm.

5.2 Practical Network Experiment

In this subsection, we evaluate the proposed MC-PSO algorithm by practical network experiment based on campus wireless network (IEEE 802.11.b WLAN). Twenty-one WiFi sniffers are deployed in a building to collect the user information from 1pm to 6 pm (over 5 hours). Each sniffer captures approximately 320 000 MAC frames. Totally 622 users are monitored working on three orthogonal channels. The number of users on the three channels is 349, 118, and 155 respectively. The activity probabilities③ of these users are recorded in Table 3. It is shown that the activity probabilities of most users are less than 1%. The average activity probability is 0.002 6.

Table 3. Parameters Setting of Practical Network Experiment

Active Probability	Number of users
0.00∼0.01	578
0.01∼0.02	15
0.02∼0.04	29

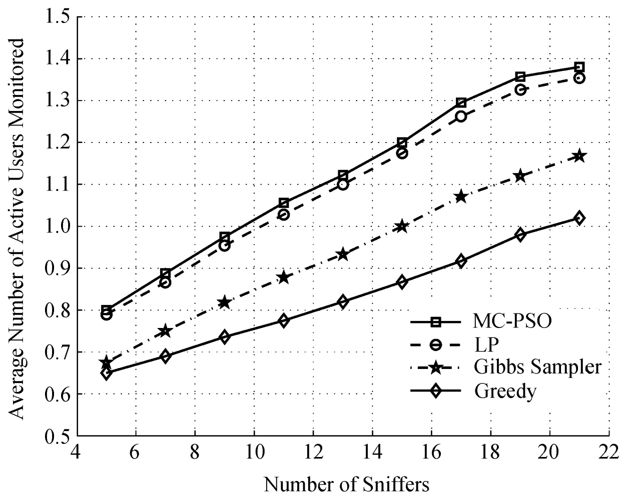

Fig.11. QoM over campus wireless network with different number of sniffers.

Fig.11 depicts the QoM of network with different number of sniffers. It is clear that the QoM (the number of monitored active users) is growing up with the increase of sniffers (from 5 to 21). Except the experiment with 21 sniffers, the other sets of experiments are conducted repeatedly with different sniffers selected randomly from the 21 sniffers, and the statistical average values of QoM are recorded and shown in Fig.11. Since the average activity probability is 0.002 6, the largest number of active users is less than 1.7 during every time slot. Compared with LP, Gibbs Sampler, and Greedy, the proposed MC-PSO exhibits its superiority and feasibility in the practical network environment.

6 Conclusions

In this paper, we investigated the channel selection for sniffers to maximize the QoM of the wireless monitoring network, which was proved to be NP-hard. A particle swarm optimization (PSO)-based solution was proposed to address the problem. A 2D mapping particle coding and its moving scheme were devised. Meanwhile, Monte Carlo method was incorporated to revise the solution and improve the convergence of the algorithm. Through extensive simulations and practical experiment, we demonstrated that the Monte Carlo enhanced PSO (MC-PSO) algorithm can solve the channel selection problem effectively, and outperforms the related algorithms evidently with fast convergence. As an ongoing work, we are reducing the computation complexity and proving the convergence performance of the algorithm in theory.

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③Active probability of a user is computed as the percentage of the user's active time in a unit time.

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