Hyper-Heuristic Genetic Algorithm for Solving Frequency Assignment Problem in TD-SCDMA

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ABSTRACT
This paper studies the frequency assignment problem (FAP) in TD-SCDMA network of mobile communications industry in China. The problem considers finding the optimal frequency allocation scheme for carriers with a limited frequency resource, such that the entire network interference is minimized. Besides, the allocation of frequencies needs to satisfy some constraints to avoid the effect of call interference within the same cell or adjacent cell. Given the formula for calculation of the network interference, we take the FAP as a constrained optimization problem and use a hyper-heuristic genetic algorithm (HHGA) to optimize the assignment of frequencies. We first define six low-level heuristics (LLHs) search strategies based on the computation of interference, and then use genetic algorithm (GA) at a high-level to find the best combination sequence of LLH strategies to reduce interferences of the overall network. GA uses two-point crossover, uniform mutation, and Minimal Generation Gap (MGG) as the generation alternation model. In order to speed up the search, we define a Tabu table to avoid repeat search of LLHs. Compared with scatter search as one of the meta-heuristic algorithm with best performance, our experimental results on real data sets of TD-SCDMA network have shown better result.

Categories and Subject Descriptors
I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search—*heuristic methods*; G.1.6 [**Numerical Analysis**]: Optimization—*Global optimization*

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General Terms
Algorithms, Experimentation, Performance

Keywords
TD-SCDMA; Mobile Communication Network; Frequency Assignment Problem; Hyper-Heuristic Genetic Algorithm

1. INTRODUCTION
TD-SCDMA (Time Division-Synchronous Code Division Multiple Access) network is the third generation wireless communications network developed by China. Compared with GSM (Global System for Mobile communications) network, TD-SCDMA has faster Internet speed and higher utilization of frequency resource. In China, there are more and more people choosing to use this network. Given a limited range of frequency bandwidth, operators always face the problem of finding the optimal frequency allocation scheme with minimal interference of the network. Such problem is called frequency assignment problem (FAP) in mobile communication network. Due to the limited frequency resource and the increasing size of the network, FAP has become a key issue in TD-SCDMA network [1,2,3].

Fig.1 describes the general composition of TD-SCDMA network, which mainly includes three parts: core network (CN), radio access network (RAN) and user equipments (UE) [4]. CN handles all voice calls, data connections and data exchanges within the network, and connections and routing choices with other external network. RAN processes functions associated with wireless, such as radio resource management, power control etc. [4]. UE is the receiver or transmitter of the wireless data. In these three parts, only RAN is related to FAP. As described in Fig.1, RAN is composed of radio network controller (RNC), Node B, cells and carriers [4]. RNC provides functions of mobility management, call processing, connection management, and switching mechanisms. Node B is equivalent to the function of base station in GSM [5], which provides radio services for cells. Cell represents a continuous geographic area, at which mobile services are provided. Normally, a Node B will transmit plural radio waves to multiple cells for communications, these cells are called co-station cells and such radio waves are called carriers. Each carrier should be assigned with a frequency for wireless communication and there are always multiple carriers in one cell. Among these carries, one is called main carrier (also called main frequency) and others are called secondary carrier (also called secondary frequency).

Most wireless communications of a cell are on the main carrier, the secondary carriers will not be enabled unless the business volume or the network interference on the main carrier exceeds its maximum limitation.

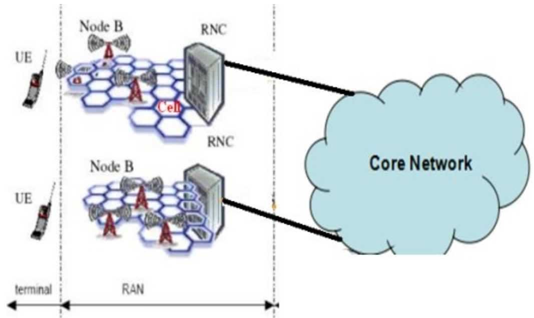


Figure 1. The General Composition of TD-SCDMA network.

In most cases of the real operations, frequencies are always reused by different carriers due to the limited frequency resources and the large requirements of the real problems. While the carries assigned with same frequencies will cause interference with each other, and such interferes would impact on call quality and data services, thus decrease the performance of the communication network. As the interference of the network varies with different frequency assignment schemes, we should find an optimal frequency assignment schema to minimize the interference of the network, so as to improve the performance of the mobile communication network.

Early scholars had regarded the frequency allocation problem as a graph coloring problem, and it was treated as a NP hard problem [6]. But this method only considered the frequency resource constraints of FAP and gave a solution without considering its quality. A high quality solution for FAP should have lower interference of the network to enable a higher quality voice call, and a balanced utilization time of all frequencies. In reality, the quality of the solution relates to every source of interference within the network environment and technical limitations. We need to find an effective way to solve FAP by considering all main factors to optimize the solution. Therefore, FAP is more like a constrained optimization problem.

There have existed contributions of FAP mostly concentrated on the GSM network, and these studies can be divided into two categories: deterministic method and heuristic method, where the latter can be further divided into meta heuristic method and hyper-heuristic method. Deterministic methods include graph coloring [7], branch cutting [8], Enumeration [9], etc. Although such methods have proved their effectiveness on dealing with small networks, they have seldom been applied to solve the large scale network problem due to the high complexity of the algorithms. Heuristic methods have proved their effectiveness on such problems [10]. Meta-heuristic methods contain tabu search [11], ant colony optimization (ACO) [5], genetic algorithm (GA) [12], scatter search (SS) [6], etc. These methods had achieved good results for solving FAP in GSM. In [6], the authors compared ACO, GA, SS and other meta-heuristic methods on a same dataset, and found that SS showed best performance for solving FAP in GSM. While these meta-heuristic algorithms had been designed for specific problems, one algorithm could not be easily applied to solve problems in different domains, so they were not generic.

Compared with meta-heuristics, hyper-heuristics have shown better perform on most optimization problems. In the literature, hyper-heuristic methods are categorized into (1) hyper-heuristics either with learning or without learning [13], or (2) constructive method and local search method [14], or (3) heuristic selection and heuristic generation [15]. Hyper-heuristic with learning changes the sequence of heuristics to call by some learning mechanism, which always achieves better performance than hyper-heuristic without learning just calling heuristics in a predetermined sequence. Local search method is more likely to find a global optimization by iteratively selecting appropriate heuristics to optimize the solution; while constructive method builds a solution incrementally by selecting heuristics. Heuristic selection selects the existing heuristics but heuristic generation can generate new heuristics from components of existing heuristics. Compared with heuristic generation, heuristic selection is independent on problem and simple to be implemented. Based on the above analysis, in this paper, we focus on hyper-heuristic with learning, local search and heuristic selection. We call this type of hyper-heuristic as hyper-heuristic in the remaining text. In contrast to meta-heuristic methods, hyper-heuristics are supposed problem independent, and easy to be implemented.

In general, hyper-heuristic methods can be divided into two layers: low level is heuristic strategies called low level heuristic (LLH), which are always some local search method based on the problems, and easy to be implemented; high level called hyper-heuristic is a selector for LLHs, which operates to find an effective LLH sequence to improve the current solution. For different optimization problems, we only need to design the LLHs according to the problems, and keep the high level unchanged. So once the hyper-heuristic (high level) has been designed, it is easy to deal with most optimization problems. In the literature, Kendall and Mohamad had proposed a hyper-heuristic method to solve FAP in GSM, they had found better solution than most other methods [16,17]. But in their work, the designed LLHs showed a slower convergence rate, and the random method used as the high level selector could not always promise a better solution. And, other works on hyper-heuristic methods to solve the FAP in mobile communication network are not so many so far.

Based on the above mentioned problems, we proposed a hyper-heuristic genetic algorithm (HHGA) in this paper to solve FAP in TD-SCDMA. In the algorithm, we designed six low level neighbor-based heuristic strategies, and use GA as the high level selector for optimizing LLH sequences. Further, we define a Tabu table to assist LLHs to avoid repeat low-level heuristic search strategy on some neighbors, through which to improve the convergence speed.

The rest of this paper is organized as follows: Chapter 2 presents the three types of frequency assignment problems in TD-SCDMA network, and gives the designed concepts, the definitions of constraints and the interference formulas in FAP; Chapter 3 introduces the generic framework of hyper-heuristic algorithm in solving optimization problems; Chapter 4 proposes a hyper-heuristic genetic algorithm for FAP in TD-SCDMA network and Chapter 5 presents and discusses the experimental results; and finally, Chapter 6 summarizes the work of this paper, and presents the future work.

2. PROBLEM DESCRIPTION

Generally, FAP contains three types of problems: (1) MS-FAP (Minimizing Span Frequency Assignment Problem), the purpose of it is to use the minimum frequency range; (2) MO-FAP (Minimizing Order Frequency Assignment Problem), it aims to use the least frequency number; (3) MI-FAP (Minimizing

Interference Frequency Assignment Problem), with its purpose to minimize the interference and improve the communication quality of the network. In this paper, we focus on the MI-FAP (The term *FAP* appears in the following text all refers to *MI-FAP*.). Before formal description of the problem, we first give some definitions and concepts related to FAP, listed in Table 1.

Table1. Definitions and Concepts Related to FAP.

Variable	Description
B	$B=\{b_1,b_2,...,b_m\}$, represents the base station set (Node B) of the network, which contains m elements.
C	$C=\{c_1,c_2,...,c_n\}$, represents a collection of cells, which contains n elements.
BC	$BC=\{bc_1,bc_2,...,bc_i,...,bc_m\}$, represents the belongs relationship between base stations and cells, where bc_i means that the collection of cells belong to the base station i.
D	$D=\{d_1,d_2,...,d_i,...,d_n\}$, represents the number of carriers that each cell has, where d_i represents that the cell i contains d_i carries.
φ_{ik}	φ_{ik} represents the frequency collection that the kth carrier of the ith cell can use, which is provided by the network operator.
f_{ik}	f_{ik} represents the frequency assigned to the kth carrier of the ith cell, $f_{ik}\in\varphi_{ik}$ .When k=1, namely f_{i1} represents the main frequency of the cell i, and other frequencies are secondary frequencies of this cell.
M	M is the interference matrix. $M[i][j]$ represents interference coefficients of cell j to cell i. This matrix is not a symmetric matrix, namely $M[i][j]\neq M[j][i](i\neq j)$.
I	The interference of the overall network, FAP should minimize the value of I .

Also, there are some constraints must be satisfied in the process of the frequency assignment. We divide these constraints into hard constraints and soft constraints. Hard constraints refer to the constraints that the solution must fulfill and those solutions met with the hard constraints are thought as feasible solutions of the problem. Soft constraints are the constraints that the solutions required to possibly satisfied, such as the utilization time of each frequency should be as close as possible, no large variance among these values. In what degree the solution meets with the soft constraints will always reflect the quality of the solution [18]. In this paper, we define and summarize the constraints of FAP in TD-SCDMA network in Table 2 [4].

Similar to GSM network, TD-SCDMA operators always split their assigned frequency bandwidth $[d_{min},d_{max}]$ into a certain number of frequencies with same intervals. These frequencies can be represented by integers like 8, 16, 24,... [17]. The task of FAP is to find a best frequency assignment schema to minimize the interference I of the entire network, with no violation of any hard constraint and satisfy the soft constraints as far as possible.

Table 2. Constraints in FAP of TD-SCDMA

Constraint type	Constraint rules	Description
Hard constraints	Limited frequency resource constraint	Each carrier can only use the frequencies provided by operator.
	Co-base station constraint	Cells of the same base station cannot have same main frequency.
	Co-cell constraint	Carriers in the same cell cannot have same frequency.
Soft constraints	Interference constraint	The less interference of the system, the better of the solution.
	Frequency distribution constraint	The utilization time of each frequency should be as close as possible, maintaining a balanced use

In this paper, we assume that two carriers would generate interference when they are assigned a same frequency. We give the equations of inference in TD-SCDMA network as follow:

$$I_{ik}=\sum_{p=1,p\neq i}^{n}\sum_{q=1}^{d_p}(M[i][p]+M[p][i])\times\alpha_{ik}^{pq},$$
$$where\ \alpha_{ik}^{pq}=\begin{cases}1, if\ (f_{ik}=f_{pq})\\0, else\end{cases}$$
$$I_i=\sum_{k=1}^{k=d_i}I_{ik} \qquad (1)$$
$$I=\sum_{i=1}^{n}I_i$$

In equation (1), I_{ik} represents the frequency interference of the kth carrier in cell i, calculated by the sum of interference generated between this carrier and all other carriers in the network except those carriers in cell i. The two terms of $M[i][p]$ and $M[p][i]$ are the coefficients between cell i and cell p, which represent the environment of wireless communication network between these two cells. Each pair of carriers in these two cells would share the same environment, that is, they use the same coefficients for computation of interferences. α_{ik}^{pq} describes whether the kth carrier in cell i and the qth carrier in cell p are assigned a same frequency, represented by 1 or 0. If the value is 1, then the two carriers would generate interference equivalent to the sum of $M[i][p]$ and $M[p][i]$. Or else, no interference would be generated between these two carriers. Besides, I_i is the interference of cell i, represented by the sum of all carriers' interference in cell i; and I denotes the overall interference of the network, which equals to the sum of all cells' interference.

Based on the above descriptions, the FAP of TD-SCDMA network can be taken as an optimization problem with no violation of any hard constraint：

$$\text{Minimize } I$$
$$\text{Subject to}$$
$$1: f_{ik} \in \phi_{ik} \quad for\ i = 1\ to\ n, k = 1\ to\ d_i$$
$$2: if\ c_i \in \mathrm{bc}_k, \mathrm{c}_j \in \mathrm{bc}_k\ \ then\ f_{i1} \neq f_{j1} \quad for\ i, j = 1\ to\ n; k = 1\ to\ m$$
$$3: f_{ij} \neq f_{ik} \quad for\ i = 1\ to\ n; j \neq k\ j, k = 1\ to\ d_i$$

The above three rules are consistent with the three hard constraints in Table 2, that is, the limited frequency resource constraint, the co-base station constraint, and the co-cell constraint. In the following, we introduce the generic framework of hyper-heuristic to explain how it works to implement optimization process with problem-independent.

3. HYPER-HEURISTIC

Compared with meta-heuristic methods, hyper-heuristics are independent of the problem and have been widely applied to solve optimization problems in different domains [16]. As described in Fig.2, hyper-heuristic methods generally include two levels operations: the low level is a set of heuristics designed for local searches, which is called low level heuristics (LLHs); the high level is a selector for LLHs, which works to find the optimal solution represented by a calling sequence of LLHs. In this paper, we only focus on hyper-heuristic methods that do not make use of domain knowledge. Therefore, there exists a barrier between the low level heuristic and the high level heuristic, meaning that no domain data flow can pass through the barrier. Only the non-domain data flow, that is, the calling sequence of LLHs can be transmitted between these two levels. This design explains why hyper-heuristic methods are independent of the problem. At the low level, an evaluation function is set to give the quality of the solution, and it can also be transmitted to the high level for evaluating the hyper-heuristic algorithm.

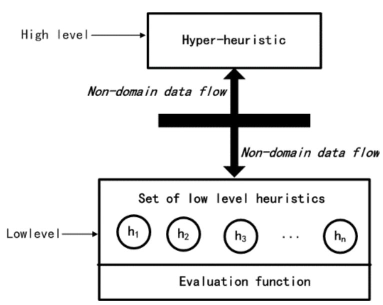


Figure 2. the framework of hyper-heuristic

The generic execution process of hyper-heuristic methods are explained as follows: first, the low level heuristics represented by h_1, h_2,…, h_n directly act on the actual problem, trying to minimize or maximize a predefined evaluation function. Next, the hyper-heuristic algorithm calls LLHs to improve the evaluation result. The evaluation result can pass through the barrier and work as the evaluation value of the high level algorithm. By keep calling LLHs with different orders and evaluating the sequences through the evaluation function, the hyper-heuristic algorithm will finally find a high quality solution with LLH sequences to solve the real problem.

When applying the hyper-heuristic method to the FAP in TD-SCDMA, hyper-heuristic at the high level deals with no domain knowledge of the FAP; it only faces a sequence of LLHs. And LLHs at the low level are general local search methods, which are carefully designed based on the actual FAP. The evaluation function at the low level is set to the overall interference of the network. The non-domain data flow represented by interference *I* can pass through the barrier between two levels, and would be evaluated by the evaluation function. Hyper-heuristic keeps calling these LLHs to minimize the interference of the network. By adjusting the calling order of LLHs, the hyper-heuristic could continuously optimize the solution.

4. HYPER-HEURISTIC GENETIC ALGORITHM for SOLVING FAP in TD- SCDMA

In the paper, we proposed a Hyper-heuristic Genetic Algorithm (HHGA) to solve the FAP in TD-SCDMA network. Following the generic framework of hyper-heuristic described in Fig.2, we first designed six LLHs of FAP at the low level, and then applied genetic algorithm as the selector of LLHs at the high level, where the chromosomes defined in GA are represented by a sequence of LLHs. In the paper, LLHs are denoted by a set of integers, where each integer represents a different LLH method. Fig.3 gives an example of chromosome in HHGA. Assume that we define four LLHs, represented by an integer set as {1,2,3,4}, the chromosome in Fig.3 would call LLHs according to the order of 2,1,3,4,1, through which to optimize the current solution.

2	1	3	4	1

Figure 3. An example of chromosome in HHGA

In the following, we will explain the design and implementation of low level heuristics and hyper-heuristic genetic algorithm.

4.1 Low Level Heuristics

Similar to the variable neighbor search (VNS) method [19], we design neighbor search-based LLHs. Each LLH starts from the current solution, and reassigns frequencies of some cells such that to find a better neighbor of the current solution. In this paper, we have designed six LLHs as follows, and the number of each LLH represents its value of the corresponding gene of a chromosome in GA. Furthermore, these LLHs can not violate any hard constraints.

1. Calculate interference of all cells according to equation (1), choose the cell with the highest interference, and then reassign the best frequency to all carriers of the cell. The best frequency for a carrier is the frequency that minimizes the interference of the carrier without changing other carriers' frequencies.
2. Same as 1, but find a better frequency. Better frequency is the frequency that the carrier reassigned with it generates less interference than the old schema.
3. Same as 1, but randomly choose a cell.
4. Same as 2, but randomly choose a cell.
5. Randomly choose a cell, and randomly choose a frequency to reassign.
6. Execute a local search for the current solution. The pseudo code of local search algorithm is given in Algorithm 1 [6].

Among these six LLHs, the fifth method is a completely random method purposing to avoid falling into local optima, and the sixth method is a local search, which aims to speed up the search process and achieve fast convergence.

Algorithm 1: Pseudo code for local search

```
input: current solution S
nextCells←{1,…,numberOfCells}
while(nextCells!=ϕ) do
    currentCells←nextCells
    nextCells←ϕ
    while(currentCells!=ϕ) do
        tmpCell←extract a random cell from currentCells
        neighbor←reassign frequencies of S in Cell tmpCell
        if(neighbor improves S) then
            S←neighbor
            nextCells+=cells interfered by tmpCell
            nextCells+=cells that interfere tmpCell
        end if
    end while
end while
return S
```

4.2 Hyper-heuristic Genetic Algorithm

At the high level, we use GA as selector for LLHs. For the GA operations, we use two-point crossover, uniform mutation, and Minimal Generation Gap (MGG[20]) as the generation alternation model. The execution of GA by MGG is described in Fig.4: ① First, choose two individuals from the initial population pool randomly, and take them as two parent of the next generation. ② Second, executes n_c times crossover on the selected two parent, through which $2n_c$ children generated, take them as the offspring. ③ Next, conducts uniform mutation on the offspring pool with a mutation probability p_m, and then generates a final offspring pool. ④ Finally, selects two individuals from the final offspring pool to replace the two parent selected in step 1. The two individuals are selected as: one is the best individual, and the other is chosen by a roulette way. The method of roulette selection is weighted by fitness. As each individual denotes a solution represented by a calling sequence of heuristics, and the solution corresponds to an interference value of the entire network, therefore, we define the fitness as the reciprocal of the expected interference I (Equation 1). The smaller the fitness is, the better the solution (individual).

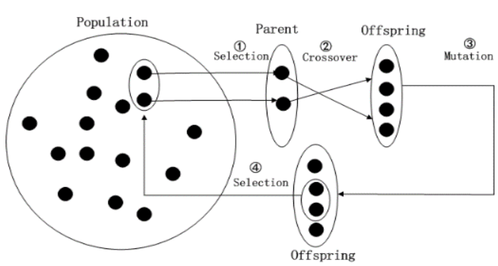


Figure 4. The Execution of GA by MGG.

Next, Algorithm 2 gives the pseudo code of HHGA for FAP in TD-SCDMA. As described in Algorithm 2, HHGA is performed in the following steps: 1) first, assume a frequency assignment task, the algorithm randomly generates a frequency assignment solution S_0, namely assigns frequencies to all the carriers randomly without violate any hard constraint, and then take S_0 as the current best solution S_{best}. 2) Generates popSize chromosomes as the GA's initial population, each chromosome is a sequence of LLHs with a fixed length L. 3) Next, randomly selects two chromosomes as parent from the initial population pool, do the crossover and mutation operations by MGG as described in Fig.4, and obtain an offspring pool. 4) For each chromosome k in the final offspring pool, applies LLHs on S_{best} according to their orders in the chromosome k, and obtains a new solution S_k. 5) For all S_k, generated in 4), compare their interferences produced by these solutions and choose two individuals with best and roulette rules to replace the parent in the initial population pool. Compare the interference produced by the best offspring solution $S_{best\_offspring}$ with the current best solution S_{best}, if it is smaller than by S_{best}, then replaces S_{best} by $S_{best\_offspring}$. 6) Repeat the steps from 3 to 5 until the predefined termination condition of GA is reached. 7) After the iteration, the algorithm returns a best solution S_{best}.

Algorithm 2: Pseudo Code for HHGA

```
Randomly generate a solution S0, Sbest←S0
Randomly generate PopSize chromosomes, which are sequences of
LLHs with a fixed length L.
while ( the termination condition of the algorithm is not reached )
    Randomly selects two chromosomes as parent from the initial
    population pool, do the crossover and mutation operations by MGG as
    described in Figure.5, and obtain an offspring pool, which contains 2nc
    chromosomes.
    for k=1 to 2nc
        Apply LLHs on Sbest according to their orders in chromosome k,
        and obtain a new solution Sk, the interference of Sk is the
        evaluation value of chromosome k. Record Sk.
    end for
    Choose two chromosomes from offspring pool to replace the parent.
    for k=1 to 2nc
      if (Interfernce(Sk)<Interfernce(Sbest))
        Sbest←Sk
      end if
    end for
end while
return Sbest
```

According to equation (1), the interference of the network is related to the interference matrix and the frequency assignment solution. Because of frequency constraints from other cells, reassignment of some cells' frequencies could not help to improve the interference of the overall network. If LLHs choose these cells to reassign, then the interference of the network could not find a better neighbor, and this search is not an effective one. In order to speed up the search process, LLHs should skip these cells. We design a Tabu table to solve this problem according to [21]. Fig.5 shows the structure of Tabu table, the base integer represents the index of a cell, and the exponent integer represents how many times this cell would not be chosen to reassign frequency. During the optimization process by HHGA, if a cell was chosen to reassign a frequency, but its interference could not be improved, this cell would be added into the Tabu table with a fixed exponent n_{max}. Each iteration the value of the exponent is reduced by 1. If the value of exponent is zero, then the cell would be removed from the Tabu table, and this cell could be chose by LLHs again. For example, 30^9 in the first grid represents that cell 30 could not be chose by LLHs in the next nine times, LLHs would skip cell 30 to speed up the searching process for better neighbors.

30^9	38^8	89^9	43^6	32^7	4^1

Figure 5. The structure of Tabu table

5. EXPERIMENTS AND ANALYSIS

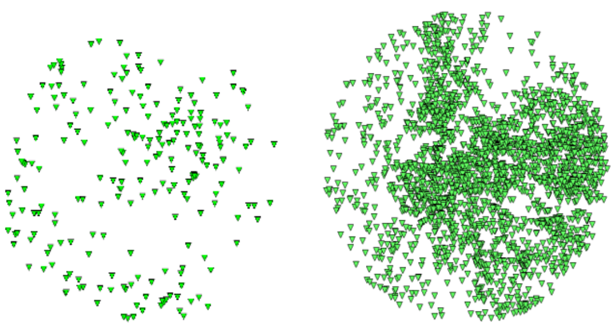
5.1 Experimental Setup

The experiments select two instances of the real TD-SCDMA network of a city in China. Instance 1 is a small network which contains 560 cells, and 2679 carriers. Instance 2 is a relative large network which contains 5025 cells and 22626 carries. Fig.6 shows the topology of these two instances. In the figure, each triangle represents a cell. Instance 1 covers a circular area with radius equal to 5km while Instance 2 covers a circular area with its radius equal to 7.5km. There are 16 frequencies available for the assignment task. As scatter search (SS) algorithm has been proved as the best meta-heuristic algorithm in [6], therefore we only compare our algorithm with the SS algorithm in the paper.

Both algorithms implemented with C# programming language. The programs run on the computer with CPU 3.2GHZ, memory 2GB. Each algorithm runs 60 minutes on instance 1, and 120 minutes on instance 2. Each algorithm runs 30 trials. Table 3 gives the parameter settings of HHGA and SS algorithms.

Table 3. Parameter settings of HHGA and SS algorithms

HHGA	SS
Population size: *PopSize*=50 Crossover times by MGG: n_c=5 Mutation probability: p_m=0.3 Maximum skip times: n_{max}=10	Population size：*PopSize*=50 Reference Set Size：*refSet size*=15 solution combination method ：uniform crossover [6]



(a) Instance 1 (b) Instance 2

Figure 6. topology of instances

5.2 Results and Analysis

5.2.1 Sensitivity test of the chromosome length on GA

First, we conduct the sensitivity test of the length of the chromosome on GA, through which to compare and analyze the impact of the length of the chromosome on HHGA. The results shown in Fig.7 proved that the length of the chromosome would affect the outcome of the interference, namely HHGA is sensitive to the length of chromosome.

Based on the experimental results in Fig.7, we found that the length of chromosome equals to 30 was a better choice for the actual network data used in instance 1 while 40 was better choice for instance 2. Therefore, when applying HHGA to solve the FAP with different network scales, we must first find an appropriate value of the length of chromosome through sensitivity test. If the length of the chromosome is too long, then the rear portion of the gene in the chromosome could not be optimized from the current solution by calling LLHs. If the length of chromosome is too short, it will weaken the effect of the crossover, and cut down the diversity of GA.

5.2.2 Comparison of Optimization Results by HHGA and SS

Next, we compared the variation of interference of HHGA and SS over time with two instances, the results represented by two groups of curves were given in Fig.8 (a) and (b), where the *x* axis was the time slot and the y axis was the average interference of the results. By comparing the curves, we found that SS converged faster than HHGA and HHGA with tabu, but the interference of frequency assignment schema by HHGA and HHGA with tabu were smaller than SS, which proved that our proposed HHGA had a better performance than SS. The curve of HHGA with tabu is below HHGA, which proved that the tabu table speeded up the process of searching.

We discussed such results in the following: although SS increases the diversity of population by using a reference set, the diversity of the population decreased with the iteration of the algorithm, thus the result may still be trapped into local optimum. HHGA optimized the frequency assignment schema by using GA to adjust the execution order of low level heuristic strategies. In the LLHs, the solution avoids local optima by considering the influence from random factors, and the local search methods with Tabu table can speed up the search process.

Further, we executed each group of experiments 30 times and compared the variation degree of the results by two statistic indexes as the standard deviation (σ) and the standard deviation coefficient ($V\sigma$), through which to confirm a robustness of the results. As given in equation (2), $V\sigma$ is defined as the ratio of the standard deviation σ to the mean $\bar{x}$, which shows a relative variation extent and would not be affected by the unit size.

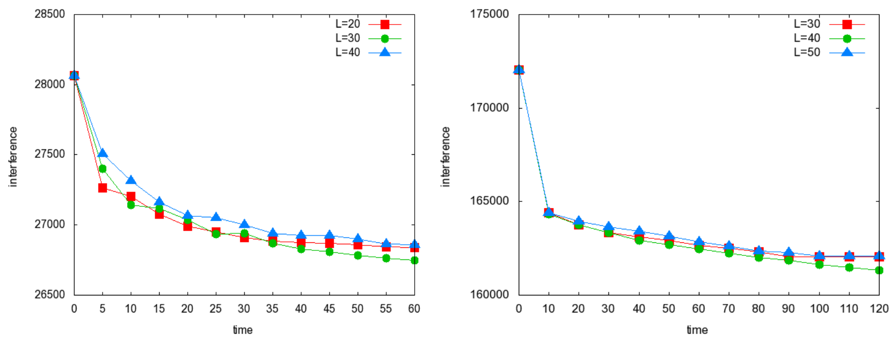
$$V\sigma = \frac{\sigma}{\bar{x}} \qquad (2)$$

The statistic results of each index were summarized in Table 4. From the results in Table 4, we found that the fluctuation of our proposed HHGA algorithm is smaller than SS, the value of $V\sigma$ were 0.20% in instance 1 and 0.30% in instance 2. The statistic results proved a robustness of our algorithm.

5.2.3 Analysis of Utilization Time of Frequencies

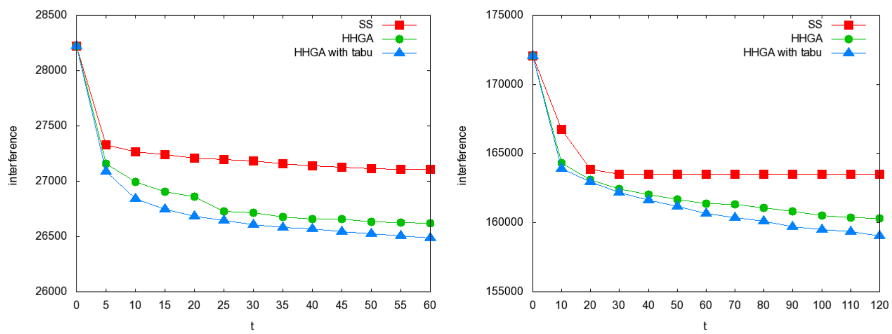
Finally, we analyzed the distribution of utilization time of frequencies assigned by HHGA. The results were shown in Figure.9, where the *x* axis represented the 16 frequencies available in the network, and the y axis gave the number of each frequency used. From the results in Figure.9, we found that the utilization times of each frequency used in both instances were very close. This result met with the soft constraints in Table 3.

From the above mentioned experiments and analysis, we can see that our proposed HHGA method has proved its effectiveness and robustness for solving the FAP in TD-SCDMA network. Furthermore, the utilization time of each frequency are very close, thus the obtained solution by HHGA is a high quality solution.



(a) Instance 1 (b) Instance 2

Figure 7. HHGA optimization process with different chromosome length

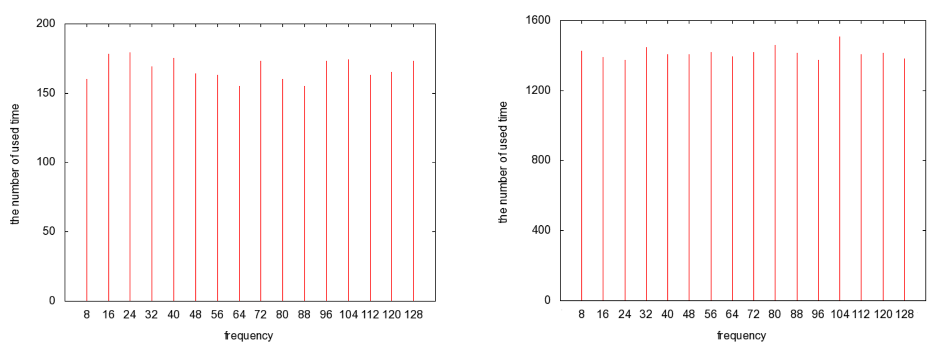


(a) Instance 1 (b) Instance 2

Figure 8. Interference curve overtime of HHGA and SS

Table 4. Average interference, standard deviation and standard deviation coefficient of the results

Algorithm	**Instance 1**			**Instance 2**		
	$\bar{x}$	σ	V_σ (%)	$\bar{x}$	σ	V_σ (%)
SS	27106.02	250.70	0.92	163494.40	590.26	0.36
HHGA	26642.89	53.04	0.20	159074.15	484.65	0.30



(a) Instance 1 (b) Instance 2

Figure 9. The times of each frequency used in the solution by HHGA.

6. CONCLUSION AND FUTURE WORK

This paper studies the frequency assignment problem (FAP) in TD-SCDMA network of mobile communications industry in China. The problem considers to find an optimal frequency assignment scheme for carriers with a limited frequency resource, such that the entire network interference is minimized. Besides, the allocation of frequencies needs to satisfy some constraints to avoid the effect of call interference within the same cell or adjacent cell. We define the formula for calculating the network interference, and take the FAP as a constrained optimization problem. To solve the FAP in TD-SCDMA network, we proposed a hyper-heuristic genetic algorithm (HHGA) to optimize the assignment of frequencies. We first defined six low-level heuristic

(LLH) search strategies for improving the interference of the FAP, and then applied genetic algorithm (GA) at a high-level to find the best combination sequence of LLH strategies to reduce the interferences of the TD-SCDMA network. GA used two-point crossover, uniform mutation, and Minimal Generation Gap (MGG) as the generation alternation model. Through evolution, GA found an optimal combination of LLHs to improve the interference of the network. In order to speed up the search, we defined a Tabu table to avoid repeat search of LLHs. We validated the performance of HHGA on real TD-SCDMA network data. Compared with scatter search as one of the best performance meta-heuristic algorithm, our experimental results on real data sets of TD-SCDMA network showed better result. Furthermore, in the solution obtained by HHGA, the utilization times of each frequency were very close. This result meets with the soft constraints in table 3. Therefore, this solution is a high quality solution.

In this study, the length of chromosome of GA used by HHGA is fixed. Due to the different scale and relation of networks, the length of chromosomes should be reset under different network environment. The optimal length of chromosome is not universal. For different applications of HHGA for solving FAP in TD-SCDMA network, the algorithm needs to adjust the length of the chromosome by many trials, which is a very troublesome work and not desirable in the actual optimization process. In future work, we intend to improve the algorithm so that the length of the chromosome can be adaptive. Such algorithms can be applied to different mobile communication networks, and will greatly improve the efficiency of frequency assignment.

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