Fixed Channel Assignment in Cellular Radio Networks Using Particle Swarm Optimization

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Abstract—**The problem of optimal channel assignment has become increasingly important because of available frequency spectrum and increasing demand for cellular communication services. This has been shown to be an NP-complete optimization problem. Many heuristic approaches including neural network, simulated annealing and genetic algorithm have been used to solve it. In this paper we propose a novel and efficient channel assignment approach, particle swarm optimization, to seek a conflict-free channel assignment such that demand is achieved and the EMC constraints are fulfilled, while number of frequency channels is minimized. Simulations on eight well-known benchmark problems showed that the PSO can effectively generate the low-band results.**

I. INTRODUCTION

In recent years, there is a continuously growing demand for mobile telecommunication. However, because of limited number of usable frequencies which are necessary for the communication between mobile users and the base stations of cellular radio networks, the efficiency in spectrum utilization becomes an important issue in frequency planning. This issue is commonly referred to as channel assignment. The objective of a channel assignment algorithm is to determine a spectrum-efficient allocation of channels to the cells while satisfying both the traffic demand and the electromagnetic compatibility (EMC) constraints. In general, there are three types of EMC constraints [1]:

- The cochannel constraint (CCC): another caller within some range using the same channel
- The adjacent channel constraint (ACC): another caller within the same region using an adjacent channel in the frequency domain
- The cosite constraint (CSC): another caller within the same region using another channel within some range.

These EMC constraints are determined by the radio frequency (RF) propagation and the spatial density of the expected traffic.

The channel assignment problem can be classified into two categories [2]: 1) fixed channel assignment (FCA), where the channels are permanently assigned to each cell; 2) dynamic channel assignment (DCA), where all available channels are allocated to the cells dynamically depending upon the current traffic demand. The major merit of FCA over DCA is that FCA, being a static technique, can afford to spend more time to come up with a better solution and is also easier to implement in practice especially under heavy traffic load condition. Since heavy traffic load is expected in the future generation cellular radio networks, an efficient FCA scheme that provides high spectrum usage efficiency is desired. The FCA problem is equivalent to the generalized graph-coloring problem. Since this problem is an NP-complete problem [3], the complexity of searching a solution for channel assignment problem grows exponentially with the number of cells. As a result, most of the investigations on this problem are based on heuristic approaches including neural network [4-6], simulated annealing [7-8] and genetic algorithms [2], [9-10].

In this paper, we represent a new approach, Particle Swarm Optimization (PSO), to solve the channel assignment problem. We consider a general cellular radio network satisfying a given channel demand without violating interference constraints, while the number of frequency channels is minimized.

The remainder of this paper is organized as follows. In Sec. II, a mathematical model is proposed to represent the channel assignment problem. Sec. III we generally describe the method of particle swarm optimization and how to modify it to operate on discrete binary variables. Afterwards, in Sec. IV some results are gained by simulation experiment. Finally, Sec. V concludes the paper and gives the direction of future work.

II. PROBLEM FORMULATION

We consider a cellular network of N cells and M channels. Without loss of generality, channels are assumed to be evenly spaced throughout the radio frequency spectrum. The contents of the cellular mobile radio map ($\mathbf{F}$ which is an $N \times M$ binary matrix) is either "0" or "1" where "0" means that the particular channel is free and "1" means that the particular channel is being assigned to a mobile call. This representation is denoted as f_{jk} where

$$f_{jk} = \begin{cases} 1 \\ 0 \end{cases} \text{if channel } k \text{ is } \left\{ \begin{matrix} \text{assigned} \\ \text{not assigned} \end{matrix} \right\} \text{to cell } j \quad (1)$$

Gamst [11] defined the compatibility matrix $\mathbf{C} = (c_{ij})$, which is an $n \times n$ symmetric matrix. c_{ij} represents the minimum separation distance in the channel domain required by channels assigned to cells i and j to avoid interference. The three constraints for the channel interference can be described by matrix $\mathbf{C}$ as:

1. CCC is described as $c_{ij} \neq 0$;
2. AAC is described as $c_{ij} \geq 2$, if i and j are adjacent cells;
3. CSC is described as $c_{ii} \geq k$, where k is a given constant.

The traffic demand requirement is represented by an n-element demand vector represented as $\mathbf{d}$. In this vector $\mathbf{d}$, each element d_i denotes the number of channels to be assigned to cell i [11].

The problem can be represented as follows: given a compatibility matrix $\mathbf{C}$, demand vector $\mathbf{d}$ and number of available channels (M), channels must be assigned to the cells such that demand is achieved and the EMC constraints are fulfilled, while number of frequency channels is minimized. A cost function derived from EMC constraints is shown below [2]:

$$C(\mathbf{F}) = \sum_{i=1}^{n}\sum_{p=1}^{m}\left(\sum_{\substack{j=1\\ j\neq i\\ c_{ij}>0}}^{n}\ \sum_{\substack{q=p-(c_{ij}-1)\\ 1\leq q\leq m}}^{p+(c_{ij}-1)} f_{jq}\right) f_{ip}$$
$$+\alpha\sum_{i=1}^{n}\sum_{p=1}^{m}\left(\sum_{\substack{q=p-(c_{ii}-1)\\ q\neq p\\ 1\leq q\leq m}}^{p+(c_{ii}-1)} f_{jq}\right) f_{ip}$$
$$+\beta\sum_{i=1}^{n}\left(\sum_{q=1}^{m} f_{iq} - d_i\right) \qquad (2)$$

where α and β are weighting factors for CSC and demand constraint respectively.

If the EMC and the traffic demand constraints are satisfied, $C(\mathbf{F})$ will achieves its minimum of zero. Thus, the objective of PSO is to search and find the solution so that $C(\mathbf{F}) = 0$.

III. Particle Swarm Optimization Algorithms

Particle Swarm Optimization is a population-based stochastic optimization technique developed by Kennedy and Eberhart [12-13]. Through cooperation and competition among the population, population-based optimization approaches often can find very good solutions efficiently and effectively. Unlike most of population-based search approaches motivated by evolution as seen in nature, e.g. genetic algorithms, evolutionary strategies and genetic programming, PSO is motivated from the simulation of social behavior [14].

Instead of using evolutionary operators to manipulate the individuals, like in other evolutionary computational algorithms, each individual in PSO flies in the search space with a velocity which is dynamically adjusted according to its own flying experience and its companion's experience, so that the individuals of the population can be expected to move towards better solution areas. Each individual is treated as a volume-less particle in the D-dimensional search space. The particles are manipulated according to the following equations:

$$v'_{id} = v_{id} + rand()*(p_{id} - x_{id}) + Rand()*(p_{gd} - x_{id}) \qquad (3)$$

$$x_{id} = x_{id} + v_{id} \qquad (4)$$

where v'_{id} is the updated velocity of particle; v_{id} is the current velocity of particle and x_{id} is current position of particle i.

Equation (3) calculates a new velocity for each particle (potential solution) based on its previous velocity v_{id}, the particle's location at which the best fitness has been achieved p_{id}, and the population global location p_{gd} at which the best fitness so far has been achieved. Equation (4) updates each particle's position in solution hyperspace. The two random numbers $rand()$ and $Rand()$ are independently generated.

In the channel assignment problem, the frequency f_{jk} is binary-selected or not selected. In such a discrete space, the concepts such as trajectory, velocity, should be redefined. Kennedy and Eberhart [15] gave the solution in terms of *changes of probabilities* that a bit will be in one state or the other. A particle moves to a state restricted to zero and one on each dimension, where each v_{id} represents the probability of bit x_{id} taking the value 1. In other words, if $v_{id} = 0.20$, then there is a twenty percent chance that x_{id} will be a one, and an eighty percent chance it will be a zero. If the previous best positions have had a zero in that bit, then $(p_{id} - x_{id})$ can be reasonably calculated as -1, 0, or +1, and used to weight the change in probability v_{id} at the next step.

The velocity update formula (3) based on the channel assignment problem is revised as follow:

$$\mathbf{V}_{id}' = \mathbf{V}_{id} + rand(\,)*(\mathbf{F}_{p_{id}} - \mathbf{F}_{id}) + Rand(\,)*(\mathbf{F}_{p_{gd}} - \mathbf{F}_{id}) \qquad (5)$$

where $\mathbf{F}_{p_{id}}$ represents the particle's location at which the best fitness has been achieved so far and $\mathbf{F}_{p_{gd}}$ represents the best particle among the neighbours at which the best fitness has been achieved so far.

The elements of $\mathbf{V}_{id}$, since they are probability, must be constrained to the interval [0.0, 1.0]. This can be accomplished by using the sigmoid function, defined as

$$sig(x) = \frac{1}{1+\exp(-x)} \qquad (6)$$

Instead of the usual position update (4), a new probabilistic update equation is used, namely

$$if\,(rand() < S(v_{id}))\, then\, x_{id} = 1; \qquad (7)$$
$$else\;\; x_{id} = 0$$

where the function $S(v_{id})$ is a sigmoid limiting transformation and $rand()$ is a quasi-random number selected from a uniform distribution in [0.0, 1.0]. By studying (6), it becomes clear that the value x_{id} will remain 0 if $S(v_{id}) = 0$. This will happen when v_{id} is approximately less than -10. Likewise, the sigmoid function will saturate when $v_{id} > 10$. To prevent this, it is recommended to clamp the value of v_{id} to the range ±4 [16]. Then probabilities will be limited to $S(v_{id})$, between 0.9820 and 0.018.

IV. RESULTS

A set of benchmark problems has been defined on a hexagonal cellular network of 21 cells as shown in Figure 1.

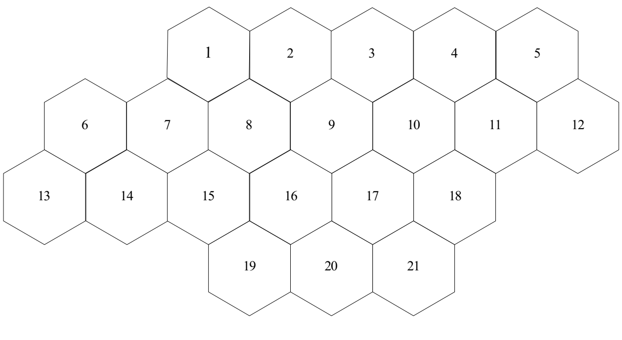

Figure 1. The 21-cell system

Demand vectors D_1 and D_2 are shown below:

D_1 = [8 25 8 8 8 15 18 52 77 28 13 15 31 15 36 57 28 8 10 13 8]

D_2 = [5 5 5 8 12 25 30 25 30 40 40 45 20 30 25 15 15 30 20 20 25]

In PSO, the position of each particle in D dimension space represents a particular assignment matrix. The swarm is therefore a set of potential solutions that 'fly' the space searching for an optimum result. The operation of the PSO algorithm would, in general, lead to nowhere. When all possible 1/0 strings for $\mathbf{F}$ matrix is allowed, the search space is so vast that it is almost impossible to find a valid optimum solution, especially when the problem size is large. In order to reduce the search space, we make some constraints on all available solutions; by assuming that these solutions satisfy the CSC (set by matrix $\mathbf{C}$) and the traffic demand (set by vector $\mathbf{D}$). Then α and β can be set to zero, leading to

$$C(F) = \sum_{i=1}^{n}\sum_{p=1}^{m}\left(\sum_{\substack{j=1\\ j\neq i\\ c_{ij}>0}}^{n}\;\sum_{\substack{q=p-(c_{ij}-1)\\ 1\le q\le m}}^{p+(c_{ij}-1)} f_{jq}\right) f_{ip} \qquad (8)$$

By exploiting the symmetry of the compatibility matrix $\mathbf{C}$, the cost function (8) can be further simplified to

$$C(F) = \sum_{i=1}^{n-1}\sum_{\substack{j=i+1\\ c_{ij}>0}}^{n}\left(\sum_{p=1}^{c_{ij}-1}\sum_{q=1}^{p-1} f_{jq}f_{ip} + \sum_{p=c_{ij}}^{m}\;\sum_{q=p-c_{ij}+1}^{p-1} f_{jq}f_{ip} + \frac{1}{2}\sum_{p=1}^{m} f_{jp}f_{ip}\right) \qquad (9)$$

The overall procedure is described as follows:

For each particle {
Repeat initializing particles in a random fashion until they satisfy CSC and traffic demand constraints;
}
Do {
For each particle {
Calculate the fitness value according to (9);
If the particle ($\mathbf{F}_i$) dominates the current $\mathbf{F}_{pid}$ then set current value as the new $\mathbf{F}_{pid}$;
}
For each particle {
Finds the local best particle as the $\mathbf{F}_{pnd}$ according the algorithms defined in section III;
Calculate particle velocity according equation (5);
Update particle position according equation (7);
}
} while maximum iterations or minimum criteria is not attained.

The results of the optimal solutions compared the results from earlier works with the PSO are in Table I. The row *Lower Bound* in Table I for each of the problems is as reported in [10]. As we have seen from this table, the PSO can solve each of the eight benchmark problems optimally. Most of the other algorithms just determined an optimal assignment only for six of the benchmark problems except genetic algorithms in [18]. In fact, problems 2 and 6 are regarded as the most difficult ones in the literature [10, 17, 18].

TABLE I.

PERFORMANCE COMPARISONS

Problem	1	2	3	4	5	6	7	8
ACC	1	2	1	2	1	2	1	2
CSC	5	5	7	7	5	5	7	7
$D_{1/2}$	D_1	D_1	D_1	D_1	D_2	D_2	D_2	D_2
Lower Bound	381	427	533	533	221	253	309	309
PSO	381	427	533	533	221	253	309	309
[17], (2005)	381	-	533	-	221	-	-	309
[18], (2003)	381	427	533	533	221	253	309	309
[19], (2001)	381	463	533	533	221	273	309	309
[20], (2001)	381	427	533	533	221	254	309	309
[21], (2000)	381	433	533	533	-	260	-	309
[10], (1999)	381	427	533	533	221	253	309	309
[2], (1998)	-	-	-	-	221	268	-	309
[22], (1997)	381	-	533	533	221	-	309	309
[23], (1997)	381	436	533	533	-	268	-	309
[24], (1996)	381	-	533	533	-	-	-	-
[25], (1996)	381	433	533	533	221	263	309	309
[26], (1994)	381	464	533	536	-	293	-	310
[5], (1992)	381	-	533	533	221	-	309	309
[9], (1989)	381	447	533	533	-	270	-	310

V. CONCLUSION

To the best of our knowledge, the first demonstration of channel assignment problem using the PSO algorithm is represented. In our previous work [27-28], the PSO algorithm has been employed to solve some wireless communication problems. It indicates better performance and faster convergence compared with other heuristic method such as neural network, simulated annealing and genetic algorithm.

At present, a more detailed comparison is underway; however the results show that the PSO is, indeed, an effective method to solve the FCA problem. The application of our algorithm to the eight well-known benchmark problems produces an optimal solution in each case.

It is felt that in the wireless communication area, the PSO will find most use in design problems for which exact methods are not available.

REFERENCES

[1] K. N. Sivarajan, R. J. McEliece, and J.W. Ketchun, "Channel assignment in cellular radio," Proc. 39th IEEE Vehicular Technology Conf., May 1989, pp.846-850.

[2] C. Y. Ngo and V. O. K. Li, "Fixed Channel Assignment in Cellular Radio Networks Using a Modified Genetic Algorithm," IEEE Trans. On Vehicular Technology, vol. 47, no.1, pp. 163-171, 1998.

[3] W. K. Hale, "Frequency assignment: theory and applications," Proc. IEEE, vol. 68, pp. 1497-1514, Dec. 1980.

[4] M. Sengoku, K. Nakano, K. Shinoda, Y. Yamaguchi and T. Abe, "Cellular mobile communication systems and channel assignment using neural networks," Proc. IEEE 33rd Midwest Symp. Circuits and Syst., pp. 411-414, Aug. 1990.

[5] N. Funabiki and Y. Takefuji, "A neural network parallel algorithm for channel assignment problems in cellular radio networks," IEEE Trans. On Vehicular Technology, vol. 41, no. 4, pp. 430-437, 1992.

[6] G. D. Lochite, "Frequency channel assignment using artificial neural networks," Proc. 8th IEE Int. Conf. Antennas and Propagation, vol. 2, pp. 948-951, 1993.

[7] M. Duque-Anton, D. Kunz and B. Ruber, "Channel assignment for cellular radio using simulated annealing," IEEE Trans. On Vehicular Technology, vol. 42, no. 1, pp. 14-21, 1993.

[8] R. Mathar and J. Mattfeldt, "Channel assignment in cellular radio networks," IEEE Trans. On Vehicular Technology, vol. 42, no. 4, pp. 647-656, 1993.

[9] W. K. Lio and G. G. Coghill, "Channel assignment through evolutionary optimization," IEEE Trans. On Vehicular Technology, vol. 45, pp. 91-96, Feb., 1996.

[10] D. Beckmann and U. Killat, "A new strategy for the application of genetic algorithms to the channel assignment problem," IEEE Trans. On Vehicular Technology, vol. 48, pp. 1261-1269, July, 1999.

[11] A. Gamst and W. Rave, "On frequency assignment in mobile automatic telephone systems," Proc. IEEE GLOBECOM, pp. 309-315, 1982.

[12] J. Kennedy and R. C. Eberhart, "Particle Swarm Optimization," Proc. IEEE International Conference on Neural Networks, Perth, Australia. pp. 1942-1948, 1995.

[13] R. C. Eberhart and J. Kennedy, "A new optimizer using particle swarm theory," Proc. The Sixth International Symposium on Micromachine and Human Science, Nagoya, Japan. pp. 39-43, 1995.

[14] Y. Shi and R. C. Eberhart, "Empirical study of particle swarm optimization," Proc. IEEE Congress on Evolutionary Computation, Piscataway, New Jersey, USA. pp. 1945-1950, 1999.

[15] J. Kennedy and R. C. Eberhart, "A discrete binary version of the particle swarm algorithm," Proc. World Multiconference on Systemics, Cybernetics and Informatics 1997, Piscataway, New Jersey, USA. pp. 4104-4109, 1997.

[16] R. C. Eberhart and J. Kennedy, "Swarm Intelligence," Morgan Kaufmann, 2001.

[17] Alireza Ghassempour Shirazi and Hamidreza Amindavar, "Channel assignment for cellular radio using extended dynamic programming," International Journal of Electronics and Communications. (In Press)

[18] Sasthi C. Ghosh, Bhabani P.Sinha and Nabanita Das, "Channel assignment using genetic algorithm based on geometric symmetry," IEEE Trans. On Vehicular Technology, vol. 52, pp. 860-875, July, 2003.

[19] G. Chakraborty, "An efficient heuristic algorithm for channel assignment problem in cellular radio networks," IEEE Trans. On Vehicular Technology, vol.50, pp.1528-1539, 2001.

[20] R. Battiti, A. Bertossi and D. Cavallaro, "A randomized saturation degree heuristic for channel assignment in cellular radio networks," IEEE Trans. On Vehicular Technology, vol. 50, pp. 364-374, 2001.

[21] D.-W. Tcha, J.-H. Kwon, T.-J. Choi and S.-H. Oh, "Perturbation-minimizing frequency assignment in a changing TDMA/FDMA cellular environment," IEEE Trans. On Vehicular Technology, vol. 49, pp.390-396, 2000.

[22] J. S. Kim, S. H. Park, P. W. Dowd and N. M. Nasrabadi, "Cellular radio channel assignment using a modified hopfied network," IEEE Trans. On Vehicular Technology, vol. 46, pp. 957-967, 1997.

[23] C. W. Sung and W. S. Wong, "Sequential packing algorithm for channel assignment under co-channel and adjacent-channel interference constraint," IEEE Trans. On Vehicular Technology, vol. 46, pp. 676-686, 1997.

[24] J. S. Kim, S. H. Park, P. W. Dowd and N. M. Nasrabadi, "Comparison of two optimization techniques for channel assignment in cellular radio network," Proc. International Conference on Communication., vol.3, pp. 1850-1854, 1995.

[25] W. Wang and C. K. Rushforth, "An adaptive local-search algorithm for the channel assignment problem," IEEE Trans. On Vehicular Technology, vol. 45, pp. 459-466, 1996.

[26] T.-M. Ko, "A frequency selective insertion strategy for fixed channel assignment," Proc. 5th IEEE Int. Symp. Personal, Indoor and Mobile Radio Commun., pp. 311-314, 1994.

[27] ZHANG Yangyang and JI Chunlin, "Particle Swarm Optimization for Base Station Placement in Mobile Communication," Proc. IEEE International Conference on Networking, Sensing and Control, pp.428-432, Taiwan, 2004.

[28] JI Chunlin and ZHANG Yangyang, "Particle Swarm Optimization for Mobile Ad Hoc Networks Clustering," Proc. IEEE International Conference on Networking, Sensing and Control (ICNSC 2004), pp.372-375, Taiwan. Mar. 21-23, 2004