International Journal of Natural and Engineering Sciences 4 (2): 51-57, 2010
ISSN: 1307-1149, E-ISSN: 2146-0086, www.nobel.gen.tr

Overview of Channel Allocation Algorithms

Mohsen Hayati Elham Hosseini

Electrical Engineering Department Faculty of Engineering, Razi University Tagh-E-Bostan, Kermansshah-67149, Iran

Corresponding author
Email:mohsen_hayati@yahoo.com

Received : March 04, 2010
Accepted : May 20, 2010

Abstract

Channel allocation is one of many ways to reduce interference in a cellular network. Reduced interference leads to increase in capacity and throughput of the system and hence good channel allocation can lead to more effective use of the spectrum. Apart from reducing interference, channel allocation algorithms can also be used to adapt to traffic changes in a network, and together with reduced interference, the traffic that can be supported is higher. In order to select efficient algorithm for solving channel allocation problem, channel allocation algorithms are introduced and evaluated in this paper.

Keywords: Channel Assignment, Cellular Communications, Dynamic Algorithm, Iterative Algorithm

INTRODUCTION

Mobility management and bandwidth management are two major research issues in a cellular mobile network. Mobility management consists of two basic components: location management and handoff management.

With the ever-increasing number of mobile users and a preassigned communication bandwidth, the problem of using the radio spectrum efficiently for cellular mobile communication has become a critical research issue in recent years [1, 2, 3, 4, 5, 6, 7, 8, 9, 10].

The key factor in the reuse of radio spectrum in the cells is the channel interference. Neglecting other influencing factors, we assume that the channel interference is primarily a function of frequency and distance. A channel can simultaneously be used by multiple base stations, if their mutual separation is more than the reuse distance, i.e., the minimum distance at which two signals of the same frequency do not interfere. In a cellular environment, the reuse distance is usually expressed in units of number of cells. Based on that, three types of interference are generally taken into consideration:

i) Co-channel interference, due to which the same channel is not allowed to be assigned to a pair of cells simultaneously which are not sufficiently far apart.

ii) Adjacent channel interference, for which adjacent channels are not allowed to be assigned to certain pairs of cells simultaneously.

iii) Co-site interference, which implies that any pair of channels assigned to the same cell must be separated by a certain minimum value.

The task of assigning frequency channels to the cells is satisfying the frequency separation constraints with a view to avoiding channel interference and using as small bandwidth as possible is known as the channel assignment problem (CAP).

Effective channel allocation is able to reduce the level of interference, reduce the call blocking probability and increase the effective data throughput of a wireless data network. Channel allocation is a Nondeterministic Polynomial time complete (NP-complete) problem and the increase in demand for wireless services has increased the base station density of networks thereby, increasing the difficulty of the channel allocation problem.

Channel Allocation algorithms can be divided into the following categories, namely, Fixed Channel Allocation (FCA), Dynamic Channel Allocation (DCA) and Hybrid Channel Allocation (HCA) [11]. In FCA, channels are allocated to a base station for its exclusive use and the allocation is usually performed prior to network operation. Since the channels are static in FCA, it is difficult to adapt to changes in interference and traffic conditions. Many different methods have been proposed as a variation of FCA, such as channel borrowing methods, channel borrowing with directional locking, and channel borrowing with ordering. In DCA, any channel in the system can be assigned to any base station when it is needed (i.e. during network operation) contingent upon a set of conditions (e.g. Compatibility Matrix) being satisfied. Unlike FCA, the base stations employing DCA do not own any particular channels and a channel is released when a call is completed. Since the channels are assigned during network operation, DCA is able to adapt to interference and traffic changes. In a circuit switched network, DCA performs better than FCA under light to moderate traffic but it performs worse than FCA under conditions of heavy traffic [11]. HCA is a combination of FCA and DCA whereby a set of channels are statically assigned to a base station as in FCA while another set are placed in a central pool and are assigned in a DCA manner. In this way, HCA is able to inherit the advantages of both DCA and FCA. Comparison between Channel Allocation methods is shown in Table 1.

Table 1. Comparison between Channel Allocation methods

Name		Traffic function	Traffic rate	signaling	Adaptability
FCA		Uniform	Low, Moderate, High	Low	Low
DCA	centralized	Non-uniform	Low, Moderate	High	Moderate
	distributed	Non-uniform	Low, Moderate	Moderate	Relatively High
HCA		Non-uniform	All	Low	High

The classification into FCA, DCA and HCA does not reveal much about the underlying algorithms. To allocate a channel to a base station, information regarding the system and the layout of the network is required. Information can be a priori and/or current information gained during network operation. The more information the scheme obtains combined with better use of the available information, will yield improved channel assignment decisions. The channel allocation algorithms can be reclassified in a Channel Allocation Matrix, which is based on the strategy used to obtain the required information used during a channel assignment. The Channel Allocation Matrix is introduced in [12] and is shown in Figure.1 (with citations to the methods that fall into each category).

The vertical axis is a measure of the degree of centralization required by the algorithm. The degree of centralization is quantified by the number of base stations required to communicate with a central controller in order to obtain the required information to make a single channel allocation decision. The horizontal axis

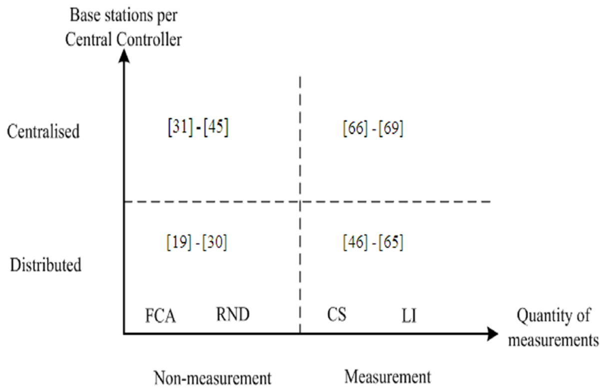

Fig. 1. Channel Allocation Matrix

represents the quantity of measurements performed by a base station and/or the subscriber's equipment in order to make a channel allocation decision. The measurements can be the interference power of a channel or an estimated SNR (or SIR) and in either case, the aim is to evaluate the interference environment prior to allocating a channel. The Channel Allocation Matrix is divided into four quadrants such as Distributed Non-measurement, Centralized Non-measurement, Distributed Measurement and Centralized Measurement.

MATERIALS and METHODS

Channel Assignment Problem

We use here, a model to represent a CAP as described by the components like Frequency separation matrix, demand vector, the number of cell, the number of available channel.

The task of allocating a set of **C** channels to a set of **B** base stations with traffic demand **D** constrained by a Compatibility Matrix X is known as a Nondeterministic Polynomial time complete (NP-complete) problem. NP-complete is a decision problem that can be solved using a nondeterministic Turing Machine in polynomial time [13].

When CAP is compared based on the objective, they can be classified into three categories which can be expressed as:

1) The first category of CAP: This class of assignment problem is known as the minimum span frequency assignment.

2) The second category of CAP: This class of assignment problem is known as the fixed bandwidth frequency assignment. There exists a different formulation of CAP where channel assignment is being looked for. When the bandwidth B of the system is given, this may even be smaller than the required lower bound on bandwidth for the given problem. Depending on B, it may or may not be possible to satisfy all the channel demands of each cell unless B is sufficiently large. Thus, a solution to this variant of CAP may, in general, leave some blocked calls. However, the objective in this case is

to minimize the call blocking as far as possible.

In both the above formulations of the CAP, the primary objective was to achieve the best possible assignment, i.e., either an optimal assignment (for the first category of CAP), or an assignment with minimal call blocking (for the second category of CAP).

3) The third category of CAP: In [14], the authors combined both of the above methods in order to combine their advantages and proposed the combined genetic algorithm (CGA) that generated a call list in each iteration, and evaluated the quality of the generated call list following the Frequency Exhaustive Assignment (FEA) strategy.

There is, however, another class of problems of real-life importance known as Perturbation-Minimizing Frequency Assignment Problem (PMFAP) [15].

Some of the researchers attempted to solve the first category of CAP from a graph theoretic view point, and proposed many heuristics [16, 17]. Later, improved approximate algorithms using neural networks, simulated annealing, tabu search [18, 19, 20] and genetic algorithms, have also been proposed to solve both the first and second categories of CAPs. For the first category of CAP, these approximate algorithms first determine an ordered list of all calls and then assign channels deterministically to the calls so as to minimize the required bandwidth [17, 21, 22, 23]. For the second category of CAP, given the bandwidth of the system, these approximate algorithms formulate a cost function such as the number of calls blocked by a given channel assignment, and then tries to minimize this cost function [20,24, 25, 26,27, 28,29, 30].

Graph Theory

The graph theoretic approach has been extensively studied and a lot of research results have been reported [31]. In the following the most important ones are summarized.

References [32,33] considered restricted classes of graphs that can model radio networks in practice. Specifically, Sen and Huson [33] argue that circle intersection graphs are a more realistic model for packet radio networks. While their assertion is valid for packet radio networks, intersection graphs of other geometric objects (e.g. regular polygons) also seem to be appropriate for modeling cellular networks and satellite networks. Here, we propose general graph theoretic models for channel assignment in packet radio networks. Our models are intersection graphs of k-plyneighborhood systems (see for example [34, 35, 36, 37, 38]) and (r,s)-civilized graphs. Following [38], a neighborhood of a point $p \in R^d$ is a closed ball of positive radius centered at p. The point p itself is called the center of the neighborhood. A neighborhood system N={B_1,B_2,…,B_n} is a finite collection of neighborhoods. For integers k, d>0, we say that N is a k-plyneighborhood system in d-dimensions if no point of R^d is strictly interior to more than k of the balls.

A civilized layout of a graph that can be drawn in a civilized manner in R^d consists of the coordinates of the vertices in R^d and the set of edges in the graph. Graphs drawn in a civilized manner have been studied in the context of random walks by Doyle and Snell [39] and in the context of finite element analysis by Vavasis [40]. Both of the above classes are reasonable models for several classes of packet radio networks when considering the channel assignment problem. To see this, consider packet radio networks in which the range of any transmitter can be considered as a circular region with the transmitter at the center of the circle. Let r denote the radius of the region corresponding to a transmitter with the maximum range. Further, it is natural to assume a minimum separation s between any pair of transmitters since the equipment carrying the transmitters cannot be colocated. Clearly, the graphs that model such packet radio networks belong to the class of (r,s)-civilized graphs. In many other realistic situations, the ratio of maximum to the minimum transmitter range is not fixed; in such cases intersection graphs of k-plyneighborhood systems are more realistic.

Intersection graphs of k-plyneighborhood systems are a strict generalization of (r,s)-civilized graphs, planar graphs and λ-precision unit disk graphs[35,41]. On the other hand, it is easy to see that for any fixed k, intersection graphs of k-ply neighborhood systems are a strict subclass of circle intersection graphs. We were motivated to study these classes of graphs for the following reasons: these are powerful enough to model realistic packet radio networks, can efficiently solve channel assignment problem, and provide a parametric family of increasingly powerful models.

Several new results for the MIND2COLOR problem appeared in the literature. Heuvel and McGuinness [31] have shown that for any planar graph with maximum node degree Δ, G^2 can be colored using at most $2\Delta + 25$ colors. Agnarsson and Halld´orsson [42] considered the minimum vertex coloring problem for G^k, the k^{th} power of a graph G. They have shown that when G is planar, G^k is $\theta(\Delta^{\lfloor k/2 \rfloor})$-inductive, where Δ is the maximum node degree of G. They also present a 2-approximation algorithm for the MIND2COLOR problem for planar graphs.

Further, they establish that for a general graph G with n nodes, it is computationally difficult to approximate the minimum coloring problem for G^k to within a factor $\Omega(n^{1/2-\varepsilon})$ for any $\varepsilon > 0$ and $k \geq 2$. Very recently, Zhou, Kanari and Nishizeki [43] have shown that for any graph G of bounded tree width and any fixed integer $k \geq 1$, the MINCOLOR problem for G^k can be solved in polynomial time.

2- Ordering Theory

In this section, six channel assignment heuristic algorithms are introduced and evaluated. They are the combinations of three channel assignment strategies, frequency and requirement and hybrid exhaustive strategy, and two cell ordering methods, node-color and node-degree ordering. A total of six non-iterative channel assignment algorithms, namely algorithms Frequency strategy/ node-color ordering (F/CR), Frequency strategy/ node-degree ordering (F/DR), Requirement strategy/ node-color ordering (R/CR), Requirement strategy/ node-degree ordering (R/DR), Frequency & Requirement strategy/ node-color ordering (FR/CR), and Frequency & Requirement strategy/ node-degree ordering (FR/DR) are introduced.

These algorithms follow the basic idea of first ordering the cells into an ordered list, then performing channel assignment. Unlike conventional approaches, cells reordered after each channel assignment according to their modified assignment difficulties.

When channel assignments with cell reordering are used, the ordered list of cells is updated every time a channel is assigned. In case of a tie, i.e. more than one cell have the same assignment difficulty, two tie resolution methods are used: (1) choose the cell to which a channel is most recently assigned first, or (2) vice versa.

What we have found is that (i) the frequency exhaustive strategy is more suitable for systems with highly non-uniformly distributed traffic, and requirement exhaustive strategy is more suitable for systems with less non-uniformly distributed traffic. (ii)The node-color ordering is a more efficient ordering method than the node-color ordering. (iii) Strategy FR with node-color reordering, or algorithm FR/CR, is the most efficient algorithm.

The frequency span found using our proposed algorithms is significantly either equal or very close to the theoretical lower bounds. Comparison between Non-iterative Algorithms is shown in Table 2.

Genetic Algorithm

Genetic algorithms (GAs) are inspired by the principle of natural selection and survival of the fittest, and constitute an alternative method for finding solutions to highly-nonlinear problems, characterized by a multimodal solutions space. GAs efficiently combine the exploration/exploitation sense of the search so as to avoid getting trapped into suboptimal local minima.

A new genetic algorithm (GA) was presented with good convergence properties and a remarkable low computational load. Such features are achieved by on-line tuning up the probabilities of mutation and crossover on the basis of the analysis of the individuals' fitness entropy. This way, a brand new method to control and adjust the population diversity is obtained. Processes in a Genetic Algorithm are shown in Fig.2.

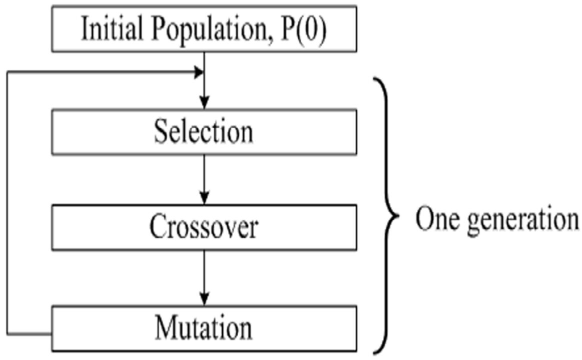

Fig.2. Processes in a Genetic Algorithm

Advantages of GA include overcoming the problem of local minima, not requiring well-behaved, convex or closed objective functions, not needing prior knowledge of Problem, having the ability to "evolve" in a direction that is not pre-defined, suitability to parallel processing, is simple to use and low memory demand requirement, and working on a population of possible solutions, while other heuristic methods use a single solution in their iterations.

Disadvantages of GA include not operating on real numbers, taking long time to achieve goal (higher CPU time cost), absence of general theory to prove population convergence to global or local minima, absence of rules available to define if a problem can be solved by GA or not, not being effective in finding precise solutions, and not being completely immune to some of difficulties such as local maxima, discontinuities, and high dimensionality.

Table 2. Comparison between Non-iterative Algorithms

Name		Complexity	Convergence	Scalability	Adaptability	Spectrum efficiency
Graph Theory		High	Moderate	Very Low	Very Low	Moderate
Ordering Theory	F/CR	High	High	Very Low	Low	High
	F/DR	Moderate	Moderate	Low	Low	Moderate
	R/CR	High	Moderate	Very Low	Low	High
	R/DR	Moderate	Low	Low	Low	Moderate
	FR/CR	High	High	Very Low	Low	Very High
	FR/DR	Moderate	Relatively High	Low	Low	High

Simulated annealing approach

To overcome the problem of local minima, a simulated annealing approach was suggested by Duque-Antn et al. [44]. Process of Simulated Annealing is shown in Fig.3. Although the approach proposed by Duque-Antn et al. is

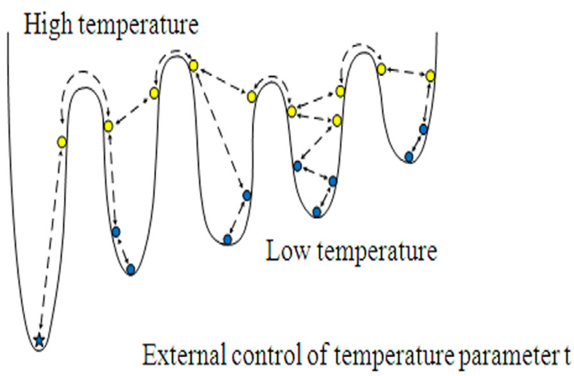

Fig.3. Process of Simulated Annealing

guaranteed to achieve the global optimum asymptotically, the convergence speed is rather slow, and a carefully designed cooling schedule is required.

Neural Network

It has been over a decade since neural networks were first applied to solve combinatorial optimization problems. During this period, enthusiasm has been erratic as new approaches are developed and (sometimes years later) their limitations are realized.

Researchers have been trying for over a decade now to make neural networks competitive with meta-heuristics[45] such as simulated annealing,[46, 47] tabu search,[48, 49] constraint logic programming,[50] and genetic algorithms,[51, 52] and they have experienced varying degrees of success. Almost every type of combinatorial optimization problem (COP) has been tackled by neural networks, and many of the approaches result in solutions that are very competitive with alternative techniques in terms of solution quality.

The idea of using neural networks to provide solutions to difficult NP-hard optimization problems [53, 54] originated in 1985 when Hopfield and Tank demonstrated that the Travelling Salesman Problem (TSP) could be solved using a Hopfield neural network [55]. The other main neural network approach to combinatorial optimization is based on Kohonen's Self-Organizing Feature Map[56]. Comparison of number of iteration with Neural Network, Simulated Annealing(SA), GA algorithms is shown in Table 3.

Comparison of performance of Iterative Algorithm is shown in Table 4.

Hybrid Algorithms

A portable and scalable approach was presented for a class of constrained combinatorial optimization problems (CCOPs) which requires to satisfy a set of constraints and to optimize an objective function simultaneously. The algorithm consists of a hybrid neural-genetic algorithm, formed by a Hop6eld Neural Network (HNN) which solves the problem's constraints, and a Genetic Algorithm (GA) for optimizing the objective function. This separated management of constraints and optimization procedures makes the proposed algorithm scalable and robust. The portability of the algorithm is given by the fact that the HNN dynamics depends only on the matrix C of constraints.

Table 4. Comparison between Iterative Algorithm

Name	Spectrum efficiency	Convergence	Complexity	Interference
Simulated Annealing	High	High	Very High	Low
Genetic Algorithm	High	High	High	Low
Neural Network	High	High	Moderate	Low

The fuzzy Hopfield neural network (FHNN) is proposed for channel assignment in wireless cellular system. Each channel is regarded as a data sample and every cell is taken as a cluster. Channels are adequately distributed to the dedicated cells while satisfying the interference constraints such as co-site constraints, adjacent channel constraints, and co-channel constraints. The goal is to avoid the interference and serve the expected traffic, which is to minimize used spectrum.

Moreover, interference prediction is a delicate task; it depends on the details of the traffic assumptions. The FHNN guarantees that the neural network will skip local minima, and in all cases will converge to the optimum arrangement of the channels. Simulation results show that the FHNN can provide an alternative approach of solving this class of channel assignment problems

CONCLUSION

In order to compare the performance of several algorithms for channel assignment, algorithm is analyzed using some well-known benchmark instances. Performance of algorithms includes complexity, convergence, scalability, adaptability, spectrum efficiency, and interference. The advantage of the first category of algorithms is that the derived channel assignment always fulfills all the interference constraints for a given demand; but it may be hard to find an optimal solution in case of large and difficult problems, even with quite powerful optimization tools. On the other hand, for the second category of algorithms, it may be impossible to minimize the cost function to the desired value of zero with the minimum number of channels, in case of very hard problems.

Acknowledgments

Authors would like to thank the Iran Telecommunication Research center (ITRC) for their financial support.

Table 3. Comparison of number of iteration with Neural Network, SA, GA algorithms

Problem	GAMS	SA		HN		HCNN		SONN		TCNN		FHNN	
	Min	Av.	min	Av.	Min	Av.	Min	Av.	Min	Av.	Min	Av.	Min
KUNZ1	28	21.6	21	22.1	21	21.1	20	22.0	21	20.6	20	20.3	20
KUNZ2	39	33.2	32	32.8	32	31.5	30	33.4	33	31.2	30	28.9	29
KUNZ3	13	13.9	13	13.2	13	13.0	13	14.4	14	13.0	13	13.0	12
KUNZ4	7	1.8	1	0.4	0	0.1	0	2.2	1	0.0	0	0.0	0

REFERENCES

[1] Agrawal D. P. and Zeng Q-A. 2002. Introduction to wireless and mobile systems: Brooks/Cole Publishing.

[2] Battiti R., Bertossi A., and Bonuccelli M. A. 1999. Assigning codes in wireless networks: Bounds and scaling properties. Wireless Networks, Vol. 5:195-209.

[3] Chen H., Zeng Q-A., and Agrawal D. P. 2003. A novel channel allocation scheme in integrated wireless and mobile networks. In Proc. of 2003 Workshop on Mobile and Wireless Networks,.

[4] Chen H., Zeng Q-A, and Agrawal D. P. 2003. An adaptive call admission and bandwidth allocation scheme for future wireless and mobile networks. In Proc. of IEEE Vehicular Technology Conference, Orlando.

[5] Chen H., Zeng Q-A. and Agrawal D. P. 2002. A novel analytical model for optimal channel partitioning in the next generation integrated wireless and mobile networks. In Proc. of the 5th ACM International Workshop on Modeling Analysis and Simulation of Wireless and Mobile Systems, Atlanta, Georgia, 120 - 127.

[6] Malladi R. and Agrawal D. P. 2002. Applications of mobile and wireless networks : current and future. Communications of the ACM, Vol. 45, No. 10:144-146.

[7] Moghe A., Sen A. and Venkatachalam A. 1999. Channel borrowing algorithm for mobile cellular networks using directional locking and load balancing. Invited paper, In Proc. of the 5th International Conference on Information Systems, Analysis and Synthesis, Orlando, Florida.

[8] Roxborough T., Medidi S. R. and Sen A. 1997. On channel assignment problem in cellular networks. In Proc. of IEEE ASILOMAR Conference Signals, Systems and Communication (ASILOMAR), Monterey, CA, Vol. 1, 630-639.

[9] Sarkar S. and Sivarajan K. N. 1998. Channel assignment algorithms satisfying co-channel and adjacent channel reuse constraints in cellular mobile networks. IEEE Trans. Vehicular Technology, Vol. 51:954-967.

[10] Mathar R. and Mattfeldt J. 1993. Channel assignment in cellular radio networks. IEEE Trans. Vehicular Technology, Vol. 42, No. 4:647-656.

[11] Katzela I. and Naghshineh M. 1996. Channel Assignment Schemes for Cellular Mobile Telecommunication Systems: A Comprehensive Survey. IEEE Personal Communications, 10-31.

[12] Horng Wong Shin and Wassell Ian J. 2002. Application of Game Theory for Distributed Dynamic Channel Allocation. In Proc. of 55th IEEE Vehicular Technology Conference (Spring 2002), Birmingham, AL, USA, vol. 1, 404-408.

[13] Garey Michael R. and Johnson David S. 1979. Computers and Intractability: A Guide to the Theory of NP-Completeness. San Francisco: W. H. Freeman and Co.

[14] Beckmann D. and Killat U. 1999. A new strategy for the application of genetic algorithms to the channel-assignment problem. IEEE Trans. Vehicular Technology, Vol. 48, No. 4: 1261-1269.

[15] Tcha D.-W., Kwon J.-H., Choi T.-J., and Oh S.-H. 2000. Perturbation-minimizing frequency assignment in a changing TDMA/FDMA cellular environment. IEEE Trans. Vehicular Technology, Vol. 49, No. 2:390-396.

[16] Sivarajan K. N., McEliece R. J. and Ketchum J. W. 1989. Channel assignment in cellular radio. Proc. of 39th IEEE Vehicular Technology Conf., 846-850.

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

[18] Hao J.-K., Dorne R., and Galinier P. 1998. Tabu search for frequency assignment in mobile radio network. J. Heuristics, Vol. 4, No. 1:47-62.

[19] Capone A. and Trubian M. 1999. Channel assignment problem in cellular systems : A new model and a tabu sarch algorithm. IEEE Trans. Vehicular Technology, Vol. 48, No. 4:1252-1260.

[20] Montemanni R., Moon J. N. J., and Smith D. H. 2003. An improved tabu search algorithm for the fixed-spectrum frequency-assignment problem. IEEE Trans. Vehicular Technology, Vol. 52, No. 3:891-901.

[21] Sivarajan K. N., McEliece R. J. and Ketchum J. W. 1989. Channel assignment in cellular radio. Proc. of 39th IEEE Vehicular Technology Conf., 846-850.

[22] Chakraborty G., 2001. An efficient heuristic algorithm for channel assignment problem in cellular radio networks. IEEE Trans. Vehicular Technology, Vol. 50, No. 6:1528-1539.

[23] Battiti R., Bertossi A., and Cavallaro D. 2001. A randomized saturation degree heuristic for channel assignment in cellular radio networks. IEEE Trans. Vehicular Technology, Vol. 50, No. 2:364-374.

[24] Duque-Anton M., Kunz D. and Ruber B. 1993. Channel assignment for cellular radio using simulated annealing. IEEE Trans. Vehicular Technology, Vol. 42, No. 1:14-21.

[25] Funabiki N. and Takefuji Y. 1992. A neural network parallel algorithm for channel assignment in cellular radio network. IEEE Trans. Vehicular Technology, Vol. 41:430-437.

[26] Kim J. S., Park S. H., Dowd P. W., and Nasrabadi N. M. 1997. Cellular radio channel assignment using a modified Hopfield network. IEEE Trans. Vehicular Technology, Vol. 46: 957-967.

[27] Kunz D. 1991. Channel assignment for cellular radio using neural networks. IEEE Trans. Vehicular Technology, Vol. 40, No. 1:188-193.

[28] Lio W. K. and Coghill G. G. 1996. Channel assignment through evolutionary optimization. IEEE Trans. Vehicular Technology, Vol. 45, No. 1:91-96.

[29] Ngo C. Y. and Li V. O. K. 1998. Fixed channel assignment in cellular radio networks using a modified genetic algorithm. IEEE Trans. Vehicular Technology, Vol. 47, No. 1:163-172.

[30] Smith K. and Palaniswami M. 1997. Static and dynamic channel assignment using neural network. IEEE J. Select. Areas Commun., Vol. 15:238-249.

[31] Van den Huevel J. and McGuinness S. 1999. Coloring the Square of a Planar Graph, Report No. LSE-CDAM-99-06, Center for Discrete and Applicable Mathematics, London School of Economics, London, UK.

[32] Ramanathan S. and Lloyd E. L. 1993. Scheduling algorithms for Multi- Hop radio networks. IEEE/ACM Trans. on Networking, (1):166–172.

[33] Sen A. and Huson M. L. 1997. A New Model for Scheduling Packet Radio Networks. Wireless Networks, (3): 71–82.

[34] Greenbaum K., Miller G. L. and Teng S. H. 1994. Moments of Inertia and Graph Separators. In Proc. of 5th Annual ACM-SIAM Symposium on Discrete Algorithms (SODA'94), Arlington, VA, 452– 461.

[35] Miller G. L., Teng S. H., Thurston W. and Vavasis S. A. 1997. Separators for sphere packings and nearest neighbor graphs. J. ACM, (44):1–29.

[36] Miller G. L., Teng S. H., and Vavasis S. A. 1991. A Unified Geometric Approach to Graph Separators. In Proc. of 32nd IEEE Symposium on Foundations of Computer Science (FOCS'91), Puerto Rico, 538–547.

[37] Spielman D. and Teng S. H. 1996. Spectral Partitioning Works: Planar Graphs and Finite Element Meshes. In 37th Annual Symposium on Foundations of Computer Science (FOCS'96), Burlington, VT, 96–105.

[38] Teng S. H. 1991. Points, Spheres, and Separators a Unified Geometric Approach to Graph Separators, Ph.D. thesis, School of Computer Science, Carnegie Mellon University, CMU-CS-91-184, Pittsburgh.

[39] Doyle P. G. and Snell J. L. 1984. Random Walks and Electric Networks, The Carus Mathematical Monographs, The Mathematical Association of America, Providence, RI.

[40] Vavasis S. A. 1991. Automatic domain partitioning in three dimensions. SIAM J. Sci. Stat. Comp., (12):950–970.

[41] Hunt H. B., Marathe M. V., Radhakrishnan V., Ravi S. S., Rosenkrantz D. J. and Stearns R. E. 1998. NC-Approximation schemes for NP and PSPACE-Hard problems for geometric graphs, J. Algorithms, (26):238–274.

[42] Agnarsson G. and Halld´orsson M. 2000. Coloring Powers of Planar Graphs. In Proc. of 11th Annual ACM-SIAM Symposium on Algorithms (SODA'2000), San Francisco, CA, 654–662.

[43] Zhou X., Kanari Y. and Nishizeki T. 2000. Generalized vertex colorings of partial ttrees. IEICE Transaction Fundamentals, Vol. E-A, No. 4:1–8.

[44] Duque-Antn M., Kunz D., Rber B. 1993. Channel assignment for cellular radio using simulated annealing. IEEE Trans. Vehicular Technology, (42):14–21.

[45] REEVES C. R. 1993. Modern Heuristic Techniques for Combinatorial Problems: Blackwell Scientific Publications, Oxford.

[46] AARTS E. H. L. and KORST J. 1989. Simulated Annealing and Boltzmann Machines: John Wiley & Sons, Essex, U.K.

[47] AARTS E. H. L. and LAARHOVEN P. J. M. 1985. Statistical cooling: A general approach to combinatorial optimization problems. Philips Journal of Research 40,:193–226.

[48] GLOVER F. 1986. Future paths for integer programming and links to artificial intelligence. Computers and Operations Research 5, 533–549.

[49] GLOVER F. 1993. A user's guide to tabu search, Annals of Operations Research 41, 3–28.

[50] VAN HENTENRYCK P. 1989. Constraint Satisfaction in Logic Programming: MIT Press, Cambridge.

[51] DAVIS L. 1991. Handbook of Genetic Algorithms: Van Nostrand Reinhold, New York.

[52] GOLDBERG D. E. 1989. Genetic Algorithms in Search Optimization, and Machine Learning: Addison-Wesley, Reading.

[53] GAREY M. R. and JOHNSON D. S. 1979. Computers and Intractability: W. H. Freeman, New York.

[54] NEMHAUSER G. L. and WOLSEY L. A. 1988. Integer and Combinatorial Optimization: John Wiley & Sons, New York.

[55] HOPFIELD J. J. and TANK D. W. 1985. Neural computation of decisions in optimization problems. Biological Cybernetics 52, 141–152.

[56] KOHONEN T. 1982. Self-Organized Formation of Topologically Correct Feature Maps. Biological Cybernetics 43, 59–69.