Transiently Chaotic Neural Networks for Channel Assignment in Cellular Mobile Communications

Sa Li and Lipo Wang
School of Electrical and Electronic Engineering
Nanyang Technological University
Nanyang Avenue, Singapore 639798
Email: {p149552752, elpwang}@ntu.edu.sg
http://www.ntu.edu.sg/home/elpwang

ABSTRACT

Recently, Chen and Aihara proposed the transiently chaotic neural network (TCNN) for solving combinatorial optimization problems, and the TCNN has shown a high solving ability for traveling salesman problem (TSP). In this paper, we are interested in the channel assignment problem (CAP) which is to assign the required number of frequency channels to each cell in a cellular mobile network in such a way that interference between channels is minimized and the demands are met. We used the TCNN to solve CAP, and simulation results show better performance than the results obtained by other algorithms.

1. INTRODUCTION

With the demand for cellular mobile communication services growing rapidly, optimal assignments of frequency channels are becoming more and more critical because the electromagnetic spectrum or frequencies allocated for this purpose are limited. Careful design for a cellular radio network can efficiently minimize interference between calls and guarantee the quality of service.

Smith and Palaniswami defined two types of CAP in [7]. CAP1 is to minimize the span of channels subject to demand and interference-free constraints. CAP2 is to minimize the severity of interferences, subject to demand constraints. CAP1 can be solved by graph coloring algorithms [2] and many neural network techniques. Funabiki used a parallel algorithm to solve CAP1 [8]. Chan et al proposed an approach based on cascaded multilayered feedforward neural networks which showed good performance in dynamic CAP1 [9]. Kim et al solved CAP1 by using a modified Hopfield network without fixed frequencies [10]. Kunz firstly used the Hopfield neural network for solving CAP2 by minimizing an energy or cost function representing interference and channel demand constraints in 1991 [1]. Smith and Palaniswami reformulated CAP2 as a generalized quadratic assignment problem [7] and found remarkably good solutions to CAP2 using simulated annealing (SA), a modified Hopfield neural network, and a self-organizing neural network.

Due to extensive research interests, a large body of work exists on chaotic neural networks ([11]-[19]). Chaotic neural networks can search very efficiently in solving the optimization problems because of its smaller search space. Chen and Aihara provided the theoretical explanation for the global searching ability of the chaotic neural network: its attracting set contains all global and local minima of the optimization problem, and since the chaotic attracting set has a fractal structure and covers only a very small fraction of the entire state space, the chaotic neural network is more efficient in finding good solutions for optimization problems compared to other global search algorithms. Chen and Aihara proposed a transiently chaotic neural network (TCNN) by introducing transiently chaotic dynamics into neural networks. In this paper, we use the TCNN to solve CAP2 and show that TCNN is an effective way for radio network planning. Here we deal with only CAP2 because in most of cases, the number of available channels is far less than the lower bound which is the minimum number of channels required for an interference-free assignment.

We organize this paper as follows. Section 2 reviews CAP2 and its mathematical formulations as given by Smith and Palaniswami [7]. In section 3, we introduce the detail of the TCNN algorithm. In section 4, we apply the TCNN to several benchmarking CAP2 data sets. Finally in section 5, we conclude this paper.

2. CAP2: A STATIC CHANNEL ASSIGNMENT PROBLEM

Suppose there are N cells in a mobile radio network and the total number of available channels is M. The channel requirements for cell i are given by D_i $(i = 1, 2, \cdots, N)$. $D^T = (D_1, D_2, \cdots, D_N)$ is called the demand matrix. We use the compatibility matrix $C = \{C_{ij}\}$ to store the interference information, where C_{ij} is the minimum frequency separation between cell i and cell j to guarantee an acceptably low signal/interference ratio in each region, $i, j = 1, 2, \cdots N$.

A neural network model with $N \times M$ neurons is used to calculate the channel assignment. We define x_{jk} as the output of each neuron: $x_{jk} = 1$, if cell j is assigned to channel k and $x_{jk} = 0$ otherwise. Here $j = 1, \cdots, N$ and $k = 1, \cdots, M$.

We considered three types of interferences in this paper: the co-channel constraint (CCC), the adjacent channel constraint (ACC), and the co-site constraint (SCC). A cost tensor $P_{ji(m+1)}$ is used to measure the degree of interference between cells j and i caused by such assignments that $x_{jk} = x_{il} = 1$ [7], where $m = |k-l|$ is the distance in the channel domain between channels k and l. The cost tensor P can be calculated by following equation:

$$P_{ji(m+1)} = \max\,(0, P_{jim} - 1) \quad , \qquad for \quad m = 1, \cdots, M-1 \quad , \tag{1}$$

where P_{ji1} is the element of the compatability matrix with the diagonal terms overwritten to zero ($P_{jj1} = 0$).
CAP2 then can be formulated as:
minimize

$$F(x) \;=\; \sum_{j=1}^{N}\sum_{k=1}^{M} x_{jk} \sum_{i=1}^{N}\sum_{l=1}^{M} P_{ji(|k-l|+1)} x_{il} \quad , \tag{2}$$

subject to

$$\sum_{k=1}^{M} x_{jk} \;= D_j \quad , \qquad \forall j = 1, \cdots, N \quad , \tag{3}$$

where $F(x)$ is the total interference.

3. TRANSIENTLY CHAOTIC NEURAL NETWORKS

The model for each neuron of TCNN is taken from [11]. The internal state of each neuron i is given by a time dependent scalar value y_{jk}. The output of each neuron x_{jk} is a fixed function f of the internal state:

$$x_{jk}(t) = \frac{1}{1 + e^{-y_{jk}(t)/\varepsilon}} \quad , \tag{4}$$

where ε is the steepness parameter of the output function ($\varepsilon > 0$).

$$y_{jk}(t+1) = k y_{jk}(t) + \alpha\Big(\sum_{i=1, i\neq j}^{N}\sum_{l=1, l\neq k}^{M} w_{jkil} x_{jk}(t) + I_{ij}\Big) - z(t)(x_{jk}(t) - I_0) \quad , \tag{5}$$

where w_{jkil} is the connection weight from neuron jk to neuron il, with $w_{jkil} = w_{iljk}$ and $w_{jkjk} = 0$; We can caculcate it as follows:

$$\sum_{i=1, i\neq j}^{N}\sum_{l=1, l\neq k}^{M} w_{jkil} x_{jk} + I_{ij} = -\partial E/\partial x_{jk} \tag{6}$$

And k is the damping factor of nerve membrane ($0 \leq k \leq 1$); α is the positive scaling parameter for inputs ; I_0 is the positive parameter. The corresponding energy function E for CAP is given by:

$$E \;= \frac{W_1}{2}\sum_{j=1}^{N}\Big(\sum_{k=1}^{M} x_{jk} - D_j\Big)^2 + \frac{W_2}{2}\sum_{j=1}^{N}\sum_{k=1}^{M} x_{jk}\sum_{i=1}^{N}\sum_{l=1}^{M} P_{ji(|k-l|+1)} x_{il}, \tag{7}$$

where W_1 and W_2 represent the relative strength (or importance)of the constraint and the interference, respectively. $z(t)$ is the self-feedback connection weight or refractory strength $z(t+1) = (1-\beta)z(t)$, where β represents the damping factor ($0 \leq \beta \leq 1$).

4. TCNN FOR VARIOUS CAP2S DATA SETS

We firstly used the EX problem suggested by Sivarajan [2]. It is divided into EX1 and EX2 as follows:

$N = 4, M = 11, D^T = (1, 1, 1, 3)$.

$N = 5, M = 17, D^T = (2, 2, 2, 4, 3)$.

The Second data set used in our simulations is the 21-cell cellular system (HEX1-HEX4) found in [3] (Fig.1).

We chose the last CAP2 generated from the topographical and morphostructure data from

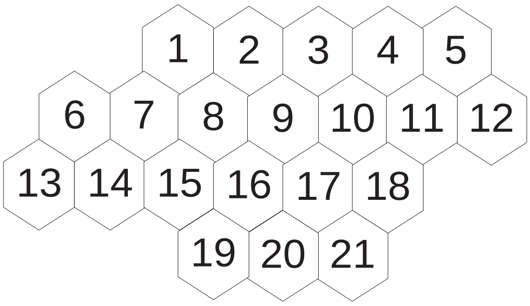

Figure 1: A 21-cell hexagonal network used in our simulations.

Table 1: The descriptions for KUNZ problems.

Problem	N	M	C	D
KUNZ1	10	30	$[C^{(3)}]_{10}$	$[D_3]_{10}$
KUNZ2	15	44	$[C^{(3)}]_{15}$	$[D_3]_{15}$
KUNZ3	20	60	$[C^{(3)}]_{20}$	$[D_3]_{20}$
KUNZ4	25	73	$C^{(3)}$	D_3

the area of 24×21 km around Helsinki, Finland [20].

Smith and Palaniswami divided this benchmarking CAP2 into four classes by considering only the first 10 regions (KUNZ1), 15 regions (KUNZ2), 20 regions (KUNZ3), and the entire area (KUNZ4)[7]. The detail is listed in Table 1.

After a large amount of simulation, we obtained better results compare to results obtained by other algorithms, which include results given in [7], i.e., the performances of GAMS/MINOS-5 (labeled GAMS), the traditional heuristics of steepest descent (SD), stochastic simulated annealing (SSA), the original Hopfield network (HN) (with no hill-climbing), the hill-climbing Hopfield network (HCHN), and the self-organizing neural network (SONN). Each of the techniques (except GAMS/MINOS-5) is run from ten different random initial conditions. We calculated the total interference found during these ten times and the assignment results have smaller values both in average total interference and minimum total interference with all CAP data set. For example, we obtained the average total interference and minimum total interference of HEX1 as 48.1 and 47, respectively. The best result among above techniques is 48.7 and 48 obtained by HCHN which is larger than 48.1 and 47, so we can give the better channel assignment. By using TCNN, we obtained the interference-free assignments of ten runs in EX and KUNZ1 problems. Also other algorithms can obtain the interference-free assignments sometime (the minimum total interferences are 0), they cannot guarantee to give the optimal assignments in each time (the average total interference for many runs are not 0). We plot the total energy function E of HEX2 in Figure 2 to show the chaotic dynamics of the system.

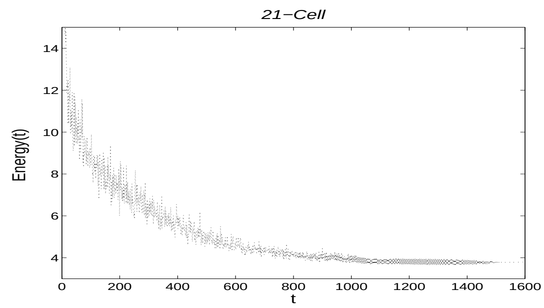

Figure 2: The Energy as a function of time in HEX2.

5. CONCLUSIONS

In this paper, we have considered the CAP and demonstrated that the transiently chaotic neural network is an effective way to solve the channel assignment problem and its simulation results show better performance than other algorithms.

The present work is concerned with only static CAPs. Implementation of the TCNN to solve other practical optimization problems, such as the dynamic CAP, will be continuously studied.

References

[1] D. Kunz, “Channel assignment for cellular radio using neural networks”, *IEEE Trans. Veh. Technol.*, vol. 40, no. 1, pp. 188-193, 1991.

[2] K. N. Sivarajan, R. J. McEliece and J.W. Ketchum, “Channel assignment in cellular radio”, *Proc. 39th IEEE Veh. Technol. Soc. Conf.*, pp. 846-850, May, 1989.

[3] A. Gamst, “Some lower bounds for a class of frequency assignment problems”, *IEEE Trans. Veh. Tech.*, vol. VT-35, pp. 8-14, Feb., 1986.

[4] W. K. Hale, “Frequency assignment: theory and application”, *Pro. IEEE*, vol. 68, pp. 1497-1514, Dec., 1980.

[5] M. Duque-Anton, D. Kunz, and B. Ruber, "Channel assignment for cellular radio using simulated annealing", *IEEE Trans. Veh. Technol.*, vol. 42, no. 1, February, 1993.

[6] K. Aihara, T. Takabe and M. Toyoda, "Chaotic neural networks", *Physics Letters A*, vol. 144, no. 6, 7, pp. 333-340, 1990.

[7] K. Smith and M. Palaniswami, "Static and dynamic channel assignment using neural network", *IEEE Journal on Selected Areas in Communications*, vol. 15, no. 2, Feb., 1997.

[8] N. Funabiki and Y. Takefuji, "A neural network parallel algorithm for channel assignment problems in cellular radio networks", *IEEE Trans. Veh. Technol.*, vol. 41, no. 4, November, 1992.

[9] P. Chan, M. Palaniswami and D. Everitt, "Neural network-based dynamic channel assignment for cellular mobile communication systems", *IEEE Trans. Veh. Technol.*, vol. 43, no. 2, May, 1994.

[10] J. Kim, S. H. Park, P. W. Dowdy and N. M. Nasrabadi, " Cellular radio channel assignment using a modified Hopfield network", *IEEE Trans. Veh. Technol.*, vol. 46, no. 4, November, 1997.

[11] L. Chen and K. Aihara, "Chaotic simulated annealing by a neural network model with transient chaos", *Neural Networks*, vol. 8, no. 6, pp. 915-930, 1995.

[12] L. Chen and K. Aihara, "Transient chaotic neural networks and chaotic simulated annealing", in M. Yamguti(ed.), *Towards the Harnessing of Chaos.* Amsterdam, Elsevier Science Publishers B.V. pp. 347-352, 1994.

[13] L. Chen and K. Aihara, "Global searching ability of chaotic neural networks", *IEEE Trans. Circuits and Systems-I: Fundamental Theory and Applications*, vol. 46, no. 8, August, pp. 974-993, 1999.

[14] H. Nozawa, "A neural network model as a globally coupled map and applications based on chaos", *Chaos,* vol. 2, no. 3, pp. 377-386, 1992.

[15] L. Wang and F. Tian, "Noisy chaotic neural networks for solving combinatorial optimization problems", *Proc. International Joint Conference on Neural Networks.* (IJCNN 2000, Como, Italy, July 24-27, 2000)

[16] L. Wang, "Oscillatory and chaotic dynamics in neural networks under varying operating conditions", *IEEE Transactions on Neural Networks,* vol. 7, no. 6, pp. 1382-1388, 1996.

[17] L. Wang and K. Smith, "On chaotic simulated annealing", *IEEE Transactions on Neural Networks,* vol. 9, no. 4, pp. 716-718, 1998.

[18] L. Wang and J. Ross, "Osillations and chaos in neural networks: an exactly solvable model", *Proc. National Academy of Sciences (USA)* vol. 87, pp. 9467-9471, 1990.

[19] L. Wang and D.L. Alkon, (eds.), *Artificial neural networks: Oscillations, chaos, and sequence processing*, (IEEE Computer Society Press), Los Alamitos, California, 1993.

[20] T. Kohonen, "Self-organized formation of topologically correct feature maps", *Biol. Cybern.*, vol. 43, pp. 59-69, 1982.