Optimal TDMA Frame Scheduling in Broadcasting Packet Radio Networks Using a Gradual Noisy Chaotic Neural Network

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Abstract. In this paper, we propose a novel approach called the gradual noisy chaotic neural network (G-NCNN) to find a collision-free time slot schedule in a time division multiple access (TDMA) frame in packet radio network (PRN). In order to find a minimal average time delay of the network, we aim to find an optimal schedule which has the minimum frame length and provides the maximum channel utilization. The proposed two-phase neural network approach uses two different energy functions, with which the G-NCNN finds the minimal TDMA frame length in the first phase and the NCNN maximizes the node transmissions in the second phase. Numerical examples and comparisons with the previous methods show that the proposed method finds better solutions than previous algorithms. Furthermore, in order to show the difference between the proposed method and the hybrid method of the Hopfield neural network and genetic algorithms, we perform a paired t-test between two of them and show that G-NCNN can make significantly improvements.

1 Introduction

The Packet Radio Network (PRN) gains more attention in recent research and industry as it is a good alternative for the high-speed wireless communication, especially in a broad geographic region [1]. The PRN shares common radio channels as the broadcast medium to interconnect nodes. In order to avoid any collision, a time-division multiple-access (TDMA) protocol has been used to schedule conflict free transmissions. A TDMA cycle is divided into distinct frames consisting of a number of time slots. A time slot has a unit time to transmit one data packet between adjacent nodes. At each time slot, each node can either transmit or receive a packet, but no more than two packets can be received from neighbor nodes. If a node is scheduled to both transmit and receive at the same time slot, a *primary* conflict occurs. If two or more packets reach one node at the same time slot, a *second* conflict occurs.

L. Wang, K. Chen, and Y.S. Ong (Eds.): ICNC 2005, LNCS 3610, pp. 1080–1089, 2005.

The BSP has been studied by many researchers [2]-[8]. In [2], Funabiki and Takefuji proposed a parallel algorithm based on an artificial neural network in a TDMA cycle with $n \times m$ neurons. In [3], Wang and Ansari proposed a mean field annealing algorithm to find a TDMA cycle with the minimum delay time. In [4], Chakraborty and Hirano used genetic algorithm with a modified crossover operator to handle large networks with complex connectivity. In [5], Funabiki and Kitamichi proposed a binary neural network with a gradual expansion scheme to find minimum time slots and maximum transmissions through a two-phase process. In [6], Yeo *et al* proposed a algorithm based on the sequential vertex coloring algorithm. In [7], Salcedo-Sanz *et al* proposed a hybrid algorithm which combines a Hopfield neural network for constrain satisfaction and a genetic algorithm for achieving a maximal throughput. In [8], Peng *et al.* used a mixed tabu-greedy algorithm to solve the BSP.

In this paper, we present a novel neural network model for this problem, i.e., gradual noisy chaotic neural network (G-NCNN). Numerical results show that this NCNN method outperforms existing algorithms in both the average delay time and the minimal TDMA length. The organization of this paper is as follows. In section 2, we formulate the broadcast scheduling problem. The noisy chaotic neural network (NCNN) model is proposed in section 3. In section 4, the proposed two-phase neural network is applied to solving the optimal scheduling problem. Numerical results are stated and the performance is evaluated in section 5. In Section 6 we conclude the paper.

2 Broadcast Scheduling Problem

We formulate the packet radio network as a graph, $G = (I,E)$, where I is the set of nodes and E is the set of edges. We follow the assumption in previous research and consider only undirected graphs and the matrix c_{ij} is symmetric. If two nodes are adjacent with $c_{ij} = 1$, then we define two nodes to be one-hop-away, and the two nodes sharing the same neighboring node to be two-hop-away. The compatibility matrix $D = \{d_{ij}\}$ consists of $N \times N$ which represents the network topology by stating the two-hop-away nodes is defined as follows:

$$d_{ij} = \begin{cases} 1 \text{ , if node } i \text{ and node } j \text{ are within two-hop-away} \\ 0 \text{ , otherwise} \end{cases}$$

We summarize the constraints in the BSP in the following two categories:

1) *No-transmission constraint* [4]: Each node should be scheduled to transmit at least once in a TDMA cycle.

2) *No-conflict constraint*: It excludes the primary conflict (a node cannot have transmission and reception simultaneously) and the secondary conflict (a node is not allowed to receive more than one transmission simultaneously).

The final optimal solution for a N-node network is a conflict-free transmission schedule consisting of M time slots. Additional transmissions can be arranged provided that the transmission does not violate the constrains. We use an $M \times N$ binary matrix $V = (v_{ij})$ to express such a schedule [3], where

$$v_{ij} = \begin{cases} 1 \text{ , if node } i \text{ transmits in slot } j \text{ in a frame} \\ \\ 0 \text{ , otherwise} \end{cases}$$

The goal of the BSP is to find a transmission schedule with the shortest TDMA frame length (i.e., M should be as small as possible) which satisfies the above constrains, and the total number of node transmissions is maximized in order to maximize the channel utilization.

3 The Proposed Neural Network Model

Since Hopfield and Tank solved the TSP problem using the Hopfield neural network (HNN), many research efforts have been made on solving combinatorial optimizations using the Hopfield-type neural networks. However, since the original Hopfield neural network (HNN) can be easily tramped in local minima, stochastic simulated annealing (SSA) technique has been combined with the HNN [10] [15]. Chen and Aihara [9][10] proposed chaotic simulated annealing (CSA) by starting with a sufficiently large negative self-coupling in the neurons and then gradually reducing the self-coupling to stabilize the network. They called this model the transiently chaotic neural network (TCNN).

In order to improve the searching ability of the TCNN, Wang and Tian [11] proposed a new approach to simulated annealing by adding decaying stochastic noise into the TCNN, i.e., a chaotic neural network with stochastic nature, a noisy chaotic neural network (NCNN). This neural network model has been applied successfully in solving several optimization problems including the traveling salesman problem (TSP) and the channel assignment problem (CAP) [11]-[14]. The NCNN model is described as follows [11]:

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

$$y_{jk}(t+1) = ky_{jk}(t) + \alpha(\sum_{\substack{i=1 \\ i \neq j}}^{N} \sum_{\substack{l=1 \\ l \neq k}}^{M} w_{jkil} x_{jk}(t) + I_{ij}) - z(t)(x_{jk}(t) - I_0) + n(t) \tag{2}$$

$$z(t+1) = (1 - \beta_1) z(t) \tag{3}$$

$$A[n(t+1)] = (1 - \beta_2) A[n(t)] \tag{4}$$

where

x_{jk} : output of neuron jk ;
y_{jk} : input of neuron jk ;
w_{jkil}: connection weight from neuron jk to neuron il, with $w_{jkil} = w_{iljk}$ and $w_{jkjk} = 0$;

$$\sum_{\substack{i=1\\i\neq j}}^{N}\sum_{\substack{l=1\\l\neq k}}^{M} w_{jkil}x_{jk} + I_{ij} = -\partial E/\partial x_{jk}\ ,\ \text{input to neuron } jk. \tag{5}$$

I_{jk} : input bias of neuron jk ;
k : damping factor of nerve membrane ($0 \leq k \leq 1$);
α : positive scaling parameter for inputs ;
β_1 : damping factor for neuronal self-coupling ($0 \leq \beta_1 \leq 1$);
β_2 : damping factor for stochastic noise ($0 \leq \beta_2 \leq 1$);
$z(t)$: self-feedback connection weight or refractory strength ($z(t) \geq 0$) ;
I_0 : positive parameter;
ε : steepness parameter of the output function ($\varepsilon > 0$) ;
E : energy function;
$n(t)$: random noise injected into the neurons, in $[-A, A]$ with a uniform distribution;
$A[n]$: amplitude of noise n.

In this paper, we combined the NCNN with a gradual scheme [5] and propose a new method called the gradual noisy chaotic neural network (G-NCNN). In this method, The number of neurons in the neural networks is not fixed, it starts with a initial number of neurons, and then the additional neurons are gradually added into the existing neural networks until the stop criteria meet. In the next section, we will discuss in detail in solving the BSP.

4 The Two-Phase Neural Network for the BSP

4.1 Energy Function in Phase I

The energy function E_1 for phase I is given as following [5]:

$$E_1 = \frac{W_1}{2}\sum_{i=1}^{N}(\sum_{k=1}^{M} v_{ik} - 1)^2 + \frac{W_2}{2}\sum_{i=1}^{N}\sum_{j=1}^{M}\sum_{\substack{k=1\\k\neq i}}^{N} d_{ik}v_{ij}v_{kj} \tag{6}$$

where W_1 and W_2 are weighting coefficients. The W_1 term represents the constraints that each of N nodes must transmit exactly once during each TDMA cycle. The W_2 term indicates the constraint that any pair of nodes which is one-hop away or two-hop away must not transmit simultaneously during each TDMA cycle.

From eqn. (2), eqn. (5), and eqn. (6), we obtain the dynamics of the NCNN for the BSP as below:

$$\begin{aligned} y_{jk}(t+1) = ky_{jk}(t) + \alpha\{-W_1(\sum_{k=1}^{M} v_{ik} - 1) \\ -W_2(\sum_{\substack{k=1\\k\neq i}}^{N} d_{ik}v_{kj})\} - z(t)(x_{jk}(t) - I_0) + n(t)\,. \end{aligned} \tag{7}$$

In order to obtain a minimal frame length which satisfies the constrains, we use a *gradual expansion scheme* in which a initial value of frame length is set with a lower bound value of M. If with current frame length there is no feasible solution which satisfied the constrains, then this value is gradually increased by 1, i.e., $M = M + 1$. The algorithm compute iteratively until every node can transmit at least once in the cycle without conflicts, then the algorithm stopped and the current value of M is the minimal frame length. In this way, the scheduled frame length would be minimized.

4.2 Energy Function in Phase II

In phase II, the objective is to maximize the total number of transmissions based on the minimal TDMA length M obtained in the previous phase. We use the energy function for phase II is defined as follow [5]:

$$E_2 = \frac{W_3}{2}\sum_{i=1}^{N}\sum_{j=1}^{M}\sum_{\substack{k=1\\k\neq i}}^{N} d_{ik}v_{ij}v_{kj} + \frac{W_4}{2}\sum_{i=1}^{N}\sum_{j=1}^{M}(1-v_{ij})^2 \tag{8}$$

where W_3 and W_4 are coefficients. W_3 represents the constraint term that any pair of nodes which is one-hop away or two-hop away must not transmit simultaneously during each TDMA cycle. W_4 is the optimization term which maximized the total number of output firing neurons.

From eqn. (2), eqn. (5), and eqn. (8), we obtain the dynamics of the NCNN for phase II of the BSP as follow:

$$\begin{aligned} y_{jk}(t+1) = ky_{jk}(t) + \alpha\{-W_3\sum_{\substack{k=1\\k\neq i}}^{N} d_{ik}v_{kj} + W_4(1-v_{ij})\} \\ -z(t)(x_{jk}(t)-I_0) + n(t) \end{aligned} \tag{9}$$

In the above models of the BSP, the network with $N \times M$ neurons is updated cyclically and asynchronously. The new state information is immediately available for the other neurons in the next iteration. The iteration is terminated once a feasible transmission schedule is obtained, i.e., the transmission of all nodes are conflict free.

5 Simulation Results

We use three evaluation indices to compare with different algorithms. One is the TDMA cycle length M. The second is the average time delay η defined as [5]:

$$\eta = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{M}{\sum_{j=1}^{M}}v_{ij}\right) = \frac{M}{N}\sum_{i=1}^{N}\left(\frac{1}{\sum_{j=1}^{M}v_{ij}}\right) \tag{10}$$

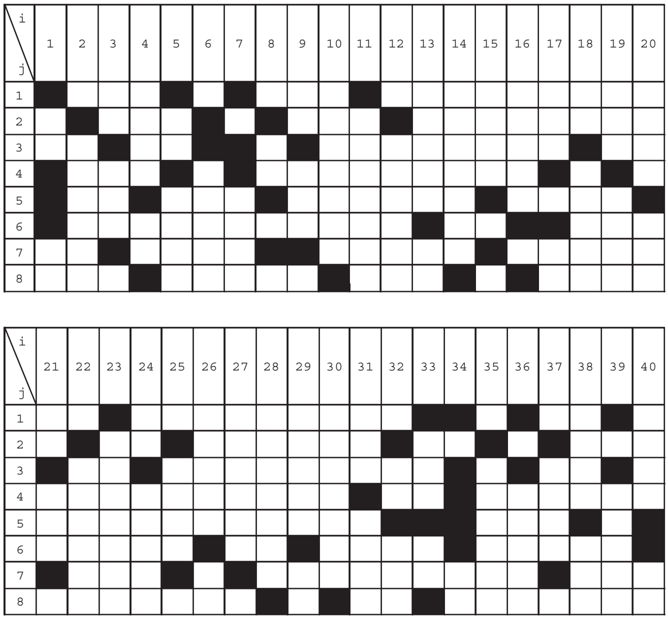


Fig. 1. Broadcasting Schedule for BM #3, the 40-node network

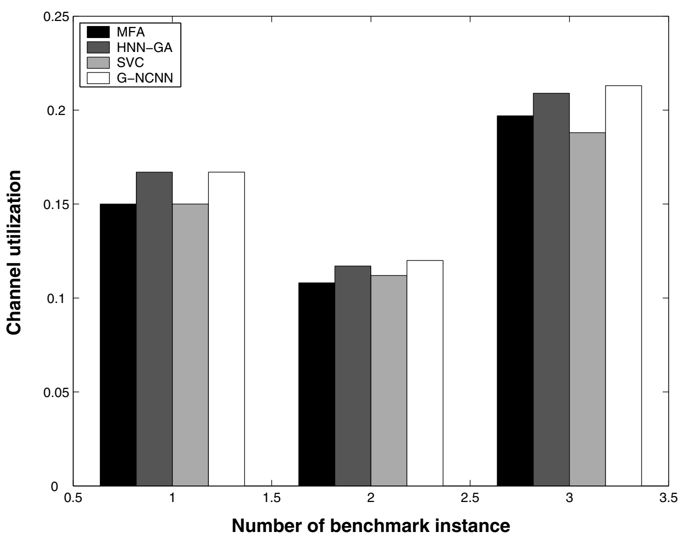
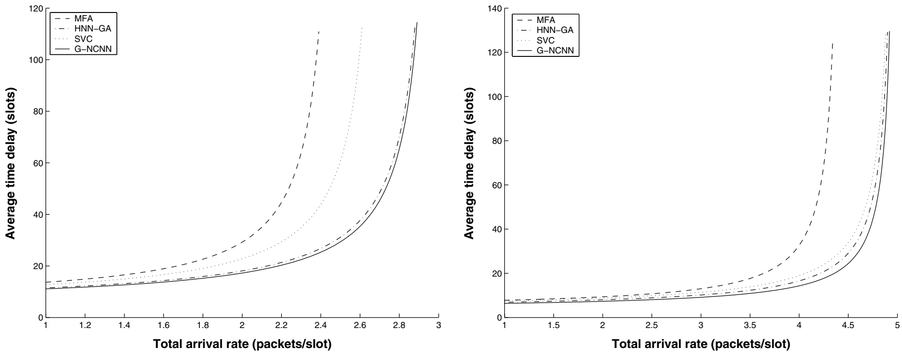


Fig. 2. Comparisons of channel utilization for three benchmark problems. 1, 2, and 3 in the horizontal axis stand for instance with 15, 30, and 40 nodes, respectively.



(a) (b)

Fig. 3. Comparison of average time delay among different approaches for two benchmark problems: (a) 30-node, (b) 40-node

where M is the time-slot cycle length and v_{ij} is the neuron output. The another definition of average time delay can be found in [3] and [6] which is calculated with the Pollaczek-Khinchin formula [16], which models the network as N $M/D/1$ queues. We will use both definitions in order to compare with other methods. The last index is channel utilization ρ, which is given by [3]:

$$\rho = \frac{1}{NM} \sum_{j=1}^{N} \sum_{i=1}^{M} v_{ij} \, . \tag{11}$$

We choose the model parameters in the G-NCNN by investigating the neuron dynamics for various combination of model parameters. The set of parameters which produces the richer and more flexible dynamics will be selected. The selection of weighting coefficients (W_1, W_2, W_3, W_4) in the energy function are based on the rule that all terms in the energy function should be comparable in magnitude, so that none of them dominates. Thus we choose the model parameters and weighting coefficients as follows:

$$\begin{aligned} k = 0.9, \alpha = 0.015, \beta_1 = 0.001, \beta_2 = 0.0002, \varepsilon = 0.004, I_0 = 0.65 \\ z_0 = 0.08, A[n(0)] = 0.009, W_1 = 1.0, W_2 = 1.0, W_3 = 1.0, W_4 = 1.0 \, . \end{aligned} \tag{12}$$

Three benchmark problems from [3] have been chosen to compared with other algorithms in [5],[6], and [7]. The three examples are instances with 15-node-29-edge, 30-node-70-edge, and 40-node-66-edge respectively.

Fig. 1 shows the final broadcast schedule for the 40-node network, where the black box represents an assigned time slot. The comparison of channel utilization in eqn. (11) for three benchmark problems is plotted in Fig. 2, which shows that

Table 1. Comparisons of average delay time η and time slot M obtained by the NCNN with other algorithms for the three benchmark problems given by [3]

	NCNN	HNN-GA	SVC	GNN	MFA
	η / M	η / M	η / M	η / M	η / M
#1	6.8 / 8	7.0 / 8	7.2 / 8	7.1 / 8	7.2 / 8
#2	9.0 / 10	9.3 / 10	10.0 / 10	9.5 / 10	10.5 / 12
#3	5.8 / 8	6.3 / 8	6.76 / 8	6.2 / 8	6.9 / 9

Table 2. Paired t-test of average time delay η (second) between the HNN-GA and the G-NCNN

Instances	Node	Edge	HNN-GA	G-NCNN
BM #1	15	29	6.84	6.84
BM #2	30	70	9.17	9.00
BM #3	40	66	6.04	5.81
Case #4	60	277	15.74	13.40
Case #5	80	397	16.33	14.48
Case #6	100	522	17.17	15.16
Case #7	120	647	17.85	16.02
Case #8	150	819	20.47	16.37
Case #9	180	966	20.04	16.38
Case #10	200	1145	20.31	17.22
Case #11	230	1226	20.36	16.58
Case #12	250	1424	20.25	17.17
T-Value = 5.22				
P-Value (one-tail) = 0.0001				
P-Value (two-tail) = 0.0003				

the NCNN can find solutions with the highest channel utilization among all algorithms. The average time delay is plotted in Fig. 3. From this figure, it can be seen that the time delay experienced by the NCNN is much less than that of the MFA algorithm in all three instances. In the 30-node and the 40-node instances, the G-NCNN can find a TDMA schedule with less delay than other methods.

The computational results are summarized in Table 1 in comparison with the hybrid HNN-GA algorithm from [7], the sequential vertex coloring (SVC) from [6], the gradual neural network (GNN) from [5] and the mean field annealing (MFA) from [3]. From this table, we can see that our proposed method can find equal or smaller frame length than other previous methods for all the three examples. In respect of the average time delay, our algorithm outperforms the other algorithms in obtaining the minimal value of η.

In order to show the difference between the HNN-GA and the NCNN, a paired t-test is performed between the two methods, as shown in Table 2. We compared the two methods in 12 cases with node size from 15 to 250, where BM #1 to BM #3 are benchmark examples and case #4 to case #12 are randomly generated instance with edge generation parameter $r = 2/\sqrt{N}$. The results show that the P-value is 0.0001 for one-tail test and 0.0003 for two-tail test. We found that the G-NCNN (mean = 13.7, standard deviation = 4.12) reported having significantly better performance than did the HNN-GA (mean = 15.9, standard deviation = 5.45) did, with T-Value $t(11) = 5.22$, P-Value < 0.05.

6 Conclusion

In this paper, we propose a gradual noisy chaotic neural network for solving the broadcast scheduling problem in packet radio networks. The G-NCNN consists of $N \times M$ noisy chaotic neurons for the N-node-M-slot problem. We evaluate the proposed method in three benchmark examples and several randomly generated instances. We compare our results with previous methods including the mean filed annealing, the HNN-GA, the sequential vertex coloring algorithm, and the gradually neural network. The results of three benchmark instances show that the G-NCNN always finds better solutions with minimal average time delay and maximal channel utilization. We also have performed a paired t-test between the G-NCNN and the HNN-GA in several randomly generated instances, the t-test results show that the G-NCNN is better than the HNN-GA in solving the BSP.

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