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TWO METHODS OF NEURAL NETWORK CONTROLLED DYNAMIC CHANNEL ALLOCATION FOR MOBILE RADIO SYSTEMS

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Abstract --Two methods of dynamic channel allocation using neural networks are investigated. Both methods continuously optimize the mobile network based on changes in calling traffic. The first method uses backpropagation model predictions to aid the channel allocator. Each cell contains a backpropagation model which provides the channel allocator a call traffic prediction allowing the channel allocator to effectively optimize the network. The second method uses the same backpropagation models along with actor-critic models to perform the channel allocation. The actor-critics learn to model traffic activity between adjacent cells real-time, and thereby learn to allocate channels dynamically between cells. The learning criterion is to minimize the number of subscribers lost from each cell. A comparison shows that both methods significantly outperform fixed channel allocation, even when the call traffic activity deviates from the previously learned models of the call traffic activity. The implementation and continual adaptation characteristics are illustrated and discussed.

I. INTRODUCTION

Neural Networks have a characteristic ability to uncover relationships between very complex nonlinear patterns. Recent research has shown that neural networks can identify very complex patterns as well as make predictions based on historical results when a similar scenario arises[2][6][8].

In this paper, neural networks are used to uncover trends in network calling traffic, which are used in channel resource allocation decisions. Two approaches are realized using a 41-cell simulated AMPS network. The first approach uses backpropagation predictions to identify spatial traffic patterns as a function of the time of day. Future traffic backpropagation predictions are fed into the channel allocator in fixed discrete time increments so that the channel allocator can uncover emerging traffic trends over a short period of time and allocate resources accordingly. This algorithm further contains a direct feedback element to accommodate dramatic traffic deviations away from backpropagation model predictions giving the mobile network real-time adaptation characteristics. The second method builds on the first method by feeding the backpropagation predictions into a real-time learner, which learns a history of traffic activity between two adjacent cells, and makes the allocation decision accordingly. The decision result is immediately reinforced based on the actual traffic results obtained from feedback on lost calls and lack of channel resources. The performance of both methods is described in this paper and is compared to fixed channel techniques. The results demonstrate the applicability of both approaches and illustrate a significant improvement over fixed channel allocation.

II. EXPERIMENTAL SETUP

Call Demand. The call demand is defined as the number of successfully assigned mobiles to valid channels in the cell plus the number of lost hand-offs and the number of lost assignments (new calls) to the cell per time of day. The equation follows:

$$CD(t) = CC(t) + LA(t) + LH(t) \tag{1}$$

where CD is the Call Demand per time of day, CC is the number of current calls assigned to channels in the cell per time of day (CC consists of the number of existing calls in the cell plus the number of successful hand-offs to the cell plus the number of successful assignments to the cell), LA is the number of Lost Assignments per time of day, LH is the number of Lost Hand-offs to the cell per time of day. A hand-off is defined as an active mobile being switched from one channel to the next when a mobile leaves a cell and enters a new cell [1]. An assignment is defined as assigning a channel to a new mobile requester.

The Project Concept. A simulation of a 41-cell network with 7 cells to a cluster (N=7) is used for the investigations. The simulation is first run in fixed channel mode with 5 channels per cell. Figure 1 illustrates the 41-cell network. Calls were generated mostly in the shaded areas during peak

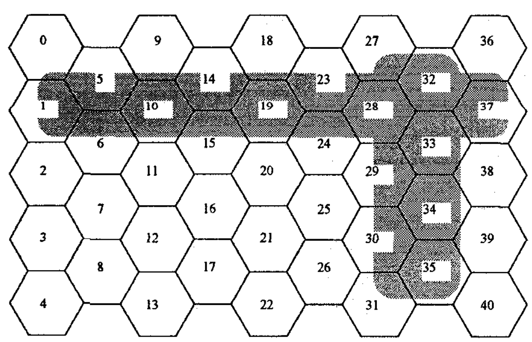

Figure 1 Forty-one cell network with cell numbers. Shaded area is the area of concentration for peak traffic.

calling times. Calls were distributed throughout the network during off-peak times. The call demand is measured per time of day (sampled every 10 minutes of simulated time) for one or more days of simulation. A daily model of the call demand in each cell is learned using backpropagation learning as described in Sections III and IV of this document. The backpropagation models are used to determine the call demand in each cell so that channels can be dynamically allocated to cells having a higher call demand from cells having a low call demand. This is the first experiment. The backpropagation predictions are then fed into actor-critics (adaptive heuristic critics) to determine whether or not a cell should lend its available channels to an adjacent requesting cell. The actor-critic is based on reinforcement learning and is described in Sections III and IV of this document [2][3]. Each cell contains an actor-critic for each of its adjacent cells. The actor-critics are punished if a cell does not have enough channels to handle its own call demand. This is the second experiment.

The General Neural Network. The artificial neural network is a mathematical, electrical or other system model of the biological neural network (the brain). Neurons are the basic building blocks of the neural network. The model of a neuron consists of multiple inputs (each input multiplied by a weight factor) and one thresholded output based on the summation of the weighted inputs. The neuron is said to "fire" if the output is in the "turned on" state, i. e., the threshold function results in an "on" state. The neurons are usually interconnected in layers. There can be any number of layers; most neural networks have at least two layers-an input layer and an output layer[4].

III. LEARNING MODULES

A. Call Demand Model Learner

Theory. The backpropagation network learns patterns based on a minimization of the squared error between the expected output vector and the actual network output vector. Backpropagation learns off line using a training set consisting of an input-output vector set. This is known as supervised learning. "Neurons" are the basic building blocks of backpropagation and are interconnected to each other in layers. Neurons typically have the sigmoid function as the threshold function [4].

Representation. Forty-one two layer backpropagation networks are used to learn the call demand in each of the 41 cells. Each network contains a 31 element input vector representing time, of which 24 components represent each hour of a day, 6 inputs represent 10 minute intervals within the hour, and 1 input to uncover any steady-state phenomena, which is always a value of one [2][3][4]. Each network has a 4 element output vector; each element is mutually exclusive. The first neuron output represents the call demand of 0-4 calls requesting channels in the cell; the second neuron output represents 5 calls requesting channels in a cell (full capacity); the third neuron output represents 6-7 calls requesting channels in a cell; the forth neuron output represents 8 or more calls requesting channels in a cell. Each network has one hidden layer consisting of 7 neurons and uses the sigmoid function as the threshold function. The backpropagation network training is stopped when the average root mean squared error [5] is sufficiently low. Once all of the networks are trained, they are used to quantify the call demand based on the time input vector. When considering all of the outputs of all of the networks, a spatial pattern emerges when looking at the large scale system. The resulting predictions are used as the input vector to the channel allocator and the Adjacent Cell Model Learners.

B. Adjacent Cell Model Learner

Theory. The actor-critic is a temporal difference method network [6]. Temporal difference method networks learn incrementally and realize the prediction over a series of incremental input vectors. The output prediction is updated as more incremental inputs are added. Conventional methods must associate input-output vector pairs. In order to learn a sequence, the conventional method must store the input-output vector pairs and learn them off-line at a later date [6].

Reinforcement Learning. The actor-critic has an external input (reinforcement) which is used for punishment or reward. The reinforcement affects the actor-critic in this way: if an action given by the critic is satisfactory, reward the critic. This increases the tendency to reproduce that action, given similar inputs to the critic [7]. If an action given by the critic is unsatisfactory, then punish the critic. Punishment suppresses the same action from being produced given similar inputs to the critic. When concerning systems in which there are long-term consequences from the current action (a long time-delay between action and feedback), the reward/punishment is formulated such that at each time-step there is some result to reward or punish based on the current action [8]. (Reinforcement in this project was immediate). The critic handles the delayed feedback (reinforcement) by computing the difference between successive predictions and by using eligibility traces [9]. Eligibility traces give the actor-critic a degenerating history that aids the algorithm in learning a delayed feedback circumstance [9].

Input Representation. Actor-Critics were used to determine whether or not a given home cell should lend a channel to a requesting adjacent cell based on the call demand of both cells projected over a 30 minute period into the future. One actor-critic was assigned for each adjacent cell to the home cell. If there were six adjacent cells to the home cell, the home cell contained six actor-critics. The home cell backpropagation output vector and the adjacent cell backpropagation output vector were concatenated to form the input vector for the actor-critic. This produced an input vector of 24 elements for the actor-critic. The first 12 elements of the input vector were always the 3 sets of backpropagation output vectors from the home cell at T+10min, T+20min, and T+30min respectively. (Recall that there is a 4 element output vector from each backpropagation algorithm). The second 12 elements of the input vector were always the 3 sets of backpropagation output vectors from the adjacent cell requesting the channel at T+10min, T+20min, and T+30min respectively. This ordering of inputs allowed the actor-critic to learn the call demand activity between the home cell and the adjacent cell [10]. Interfering cells were polled for open channels prior to the home cell-adjacent cell lending decision. If, and only if, there was an open channel in the interfering cell(s) to block, then an actor-critic decision was made regarding lending a channel to the adjacent cell. The interfering cells were removed from the actor-critic decision criteria. Channel borrowing, channel blocking, channel lending, and caller activity in interfering cells could not be adequately related to the decision in the home cell-adjacent cell lending criteria.

Output/Reinforcement Representation. The output of the actor-critic was interpreted in the following way: If the output was -1, do not lend a channel to the adjacent cell. If the output was 1, lend the channel to the adjacent cell. The feedback to the actor-critic was formed by whether or not the home cell contained enough channels to handle the call demand. The number of channels in the home cell blocked by external cells was removed from the channel calculation for the feedback. Blocked channels in the home cell could not be related to the properties of the call demand in the adjacent cell/home cell actor-critic decision. The feedback (reinforcement) was only given to actor-critics who previously made a lending decision. The reinforcement to the actor-critic is as follows: -1 (punishment) was given if there were not enough channels for the call demand in the home cell averaged over 10 minute periods; 0 otherwise. The equation for finding the number of lost calls over a 10 minute interval is as follows:

$$LC_{10\,\mathrm{min}} = \sum_{s=1}^{20} LA(t_s) + \sum_{s=1}^{20} LH(t_s) - \sum_{s=1}^{20} BC(t_s) \qquad (2)$$

where $LC_{10\,\mathrm{min}}$ is the number of lost calls over a 10 minute period, BC is the number of blocked channels and t_s is the time at sample s. There are 20 samples taken in a 10 minute period. Therefore, the lost calls per sample is $LC_{10\,\mathrm{min}}/20$. If $LC_{10\,\mathrm{min}}/20>0$, the reward is -1, 0 otherwise. This reinforcement is similar to the method employed by Franklin [2][3].

IV. DYNAMIC CHANNEL ALLOCATION

A. Dynamic Allocation Using the Call Demand Model Learner

The Call Demand Learner Implementation. The call demand data from the fixed channel allocation simulation was used for the call demand model learner training data. Once the off-line learning took place, the adaptive simulation was run using the call demand model learner outputs as predictions for allocating channels 10 minutes into the future, see Figure 2. The 41 cells were polled by inputting the time vector at T+10min time into each cell's call demand model learner and storing the predictions for later use. The 41 cells were polled to see if any of the cells were predicted to have low call demand (low traffic), meaning that they would have an excess of channels to lend. Once a "home" cell with available channels was found, the adjacent cells to the "home" cell were then checked to see if they were requesting any channels. If channels were being

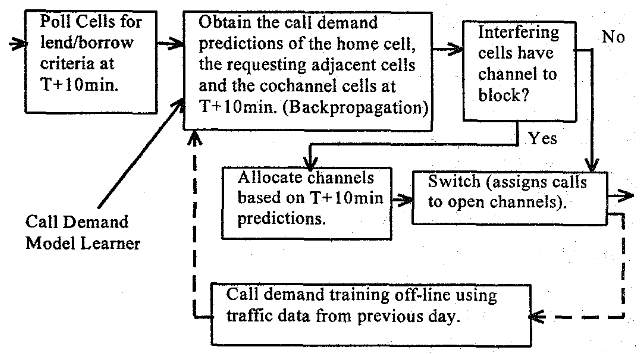

Figure 2 Mobile Telephone Switching Office with the Call Demand Model Learner.

requested by an adjacent cell, then the cochannel cells to the "home" cell closest to the adjacent requesting cell were checked for channels which could be blocked. Lending a channel causes severe interference in cochannel cells, so the same channels in the cochannel cells need to be disabled. The cochannel cells were checked using the polling data and present data, which was a prediction from the call demand model learner 10 minutes into the future. Once it was known that there were open channels in the cochannel cells to block, a check was made to see if the channels were the same frequency as the home cell. If the channels were different, hand-offs were made within the cochannel cells to free up the particular channel targeted for blocking. (The hand-offs were made with channels in the same cell.) The "home" cell then loaned the channel to the requesting adjacent cell and blocked out the corresponding frequencies in the cochannel interfering cells. This pattern was repeated for each cell until all cells were checked and available channel resources were exhausted. This series of events was repeated every 10 minutes in the simulation. Prior loaned channels were returned to their "home" cells when the predictions in the borrowing cells were to not borrow, i.e. call demand <= 5. Channels were returned to their "home" cells and blocked channels in the cochannel cells were re-enabled as soon as the borrowed channels were released from ongoing mobiles.

B. *Dynamic Channel Allocation with the Call Demand Model Learner and the Adjacent Cell Model Learner.*

The Adjacent Cell Learner Implementation. The adjacent cell model learner (actor-critic) was consulted after the previously mentioned loaning criteria was satisfied, i.e., a home cell channel was available to lend and the cochannel cells could block out the same channel, see Figure 3. There was one adjacent cell model learner for each of the adjacent cells to the home cell. The actor-critics were trained prior to being incorporated into the system to either lend channels all of the time or to not lend at all. This is similar to the initial training performed by Franklin [2]. All of the actor-critics learned these patterns successfully. The actor-critics were integrated into the same system as mentioned in the Call Demand Model Learner Implementation section. When a home cell was found with available channels to lend and an

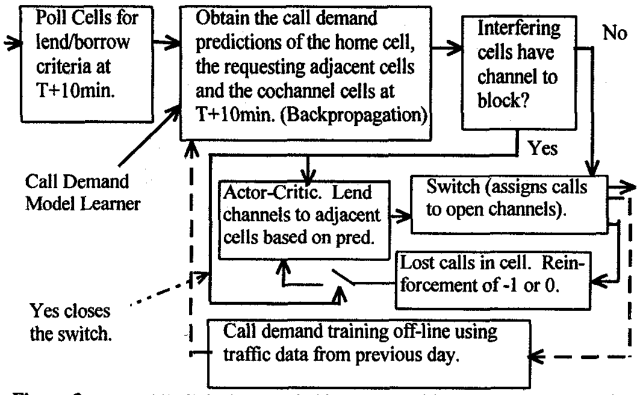

Figure 3 Mobile Telephone Switching Office with Backpropagation and Actor-Critic.

adjacent cell was requesting channels from the home cell, the cochannel cells were checked as mentioned previously. If these checks all passed, the output prediction from the backpropagation was fed into the actor-critic to determine whether or not to lend the channel. The lending took place as mentioned previously. The performance was compared to that of the fixed channel allocation system, and the results are discussed in the following section.

V. EXPERIMENTAL RESULTS AND DISCUSSION

A. Call Demand Model Learner Channel Allocation.

100% of the Calls During Peak Time Periods in 75% of the Peak Geographical Areas. The backpropagation networks were trained to this call traffic scenario and were not retrained for the rest of the project for any of the other experiments (including those containing actor-critics). Figure 4 shows the call demand generated by the simulation. The Fixed Channel Allocation (FCA) and Dynamic Channel Allocation (DCA) one day simulations placed 100% of the peak calls in 75% of the peak geographic areas (refer to Figure 1). The constancy in the simulations allows a direct comparison of the results. The plot in Figure 5 shows the lost calls per time of day for the FCA. Figure 6 shows the lost calls per time of day for the same simulated day but with the call demand model learners (backpropagation) in place. Notice that during the peak periods (around 500 minutes and 1100 minutes) the number of lost calls per time of day was reduced by about 20 mobiles per time of day, resulting in an increased network capacity. The total number of lost calls for the day was reduced from 3071

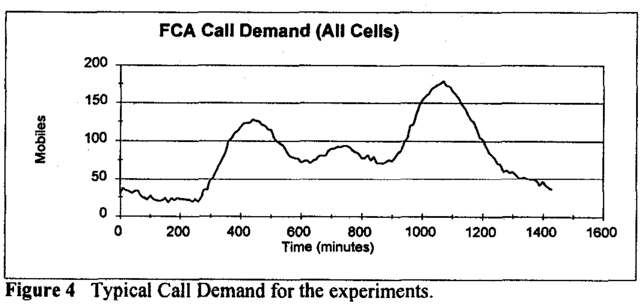

Figure 4 Typical Call Demand for the experiments.

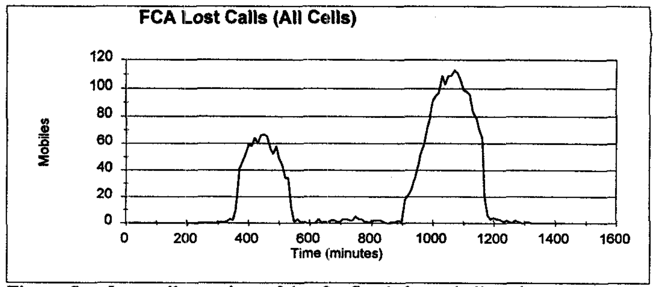

Figure 5 Lost calls per time of day for fixed channel allocation.

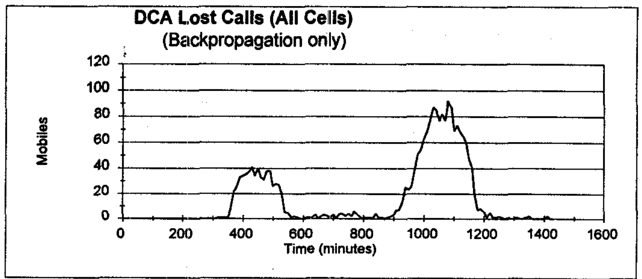

Figure 6 Lost calls per time of day for dynamic channel allocation with the call demand model learners (backpropagation).

lost calls/11721 total calls to 2151 lost calls/11234 total calls (refer to Figure 7). Further experimentation was performed by changing the distribution of traffic spatially and by time-shifting the call demand generation function[11]. The results are highlighted in the section VI.

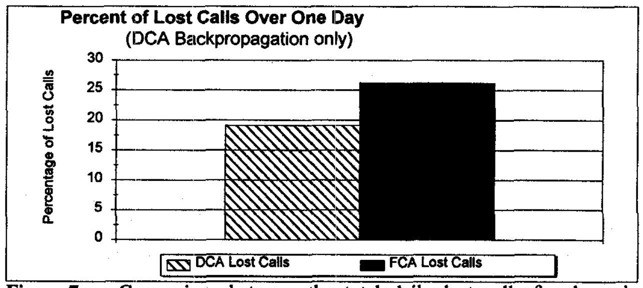

Figure 7 Comparison between the total daily lost calls for dynamic channel allocation versus fixed channel allocation.

B. Adjacent Cell Model Learner and Call Demand Learner Channel Allocation.

100% of the Calls During Peak Time Periods in 75% of the Peak Geographical Areas. The call demand for this experiment was similar to that in Figure 4. The actor-critics were trained to either lend channels all of the time or not lend at all prior to this experiment. The backpropagation networks were not retrained for this project; the same weights were used as in the first DCA experiment. The call demand for both simulations is similar. The reduction was from 3071 lost calls/11721 total calls to 2399 lost calls/11344 total calls. This is about a 5% reduction in the total lost calls. Figure 8 shows the lost calls for the DCA with backpropagation and actor-critic (compare with Figures 5 and 6). The differences in total lost calls are shown in Figure 9 (compare with Figure 7). The lost call reduction amount, however, was less than that of the

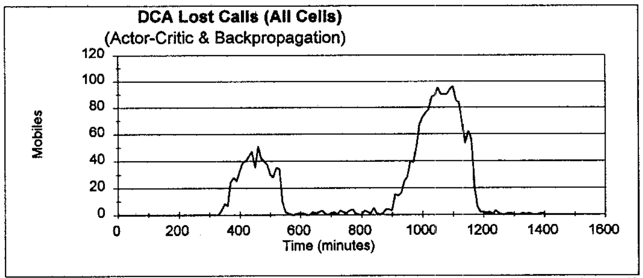

Figure 8 Lost calls for dynamic channel allocation with both the call demand model learners and the adjacent cell model learners.

previous DCA experiment with only the backpropagation in place, with 100% of the peak calls being placed in 75% of the peak areas. Further experimentation was performed by time-shifting the call traffic[11]. The results are summarized in the next section.

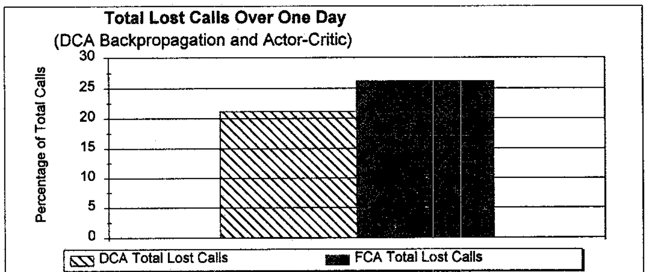

Figure 9 Comparison of the lost calls between fixed channel allocation and dynamic channel allocation with both the call demand model learners and the adjacent cell model learners.

VI. SUMMARY

A. Results of DCA with Backpropagation.

The 41 backpropagation networks were trained successfully using traffic (call demand) data from a simulated day. Once the traffic models were trained, they were incorporated into the Mobile Telephone Switching Office (MTSO) and used for dynamically allocating channels spatially to cells having a high traffic load. Further experimentation illustrated adaptation to traffic changes. The MTSO successfully accommodated spatial changes in the calling traffic from the learned patterns. The traffic time shift experiment did not adapt as well to the traffic changes when compared to the DCA containing just the backpropagation algorithms, however, it still outperformed Fixed Channel Allocation (FCA). Several models of call demand were successfully developed using 41 different learned backpropagation networks, demonstrating the applicability of this method. These experiments illustrate the use of conventional learning methods which rely on input/output training sets in a dynamical large scale cellular network. While these results look promising, more experimentation is needed, especially concerning adaptation (the ability of the MTSO to adapt to different call demand traffic patterns, different from the training data patterns.)

B. Results of DCA with Backpropagation and Actor-Critic.

The actor-critics were successfully trained off-line and incorporated along with the backpropagation models into the MTSO. The results further illustrated that improvements to the feedback would improve the system performance. Further experimentation gave evidence that the MTSO containing the actor-critics showed a favorable response to the call traffic time shift. The MTSO showed no further degradation in the network capacity from the time shift compared to the experiment without the time shifted traffic. More experimentation is needed to increase the confidence of these results, particularly, the adaptation to geographical traffic changes and time related changes in traffic.

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