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Abstract

In this paper, a methodology is presented for designing an adaptive fuzzy logic controller based on neural networks. The neuro-fuzzy controller is first trained using data from an approximate analytical model of a cellular network then the controller is fine tuned and adapted to the unique cell dwell time and call holding time distributions of a particular cell in the network. Different cell dwell time distributions are considered for training the neuro-fuzzy controller. A neuro-fuzzy method that only relies on a limited amount of measured data for training purposes is also presented.

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NEURO-FUZZY ADMISSION CONTROL IN CELLULAR NETWORKS

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ABSTRACT

In this paper, a methodology is presented for designing an adaptive fuzzy logic controller based on neural networks. The Neuro-Fuzzy controller is first trained using data from an approximate analytical model of a cellular network then the controller is fine tuned and adapted to the unique cell dwell time and call holding time distributions of a particular cell in the network. Different cell dwell time distributions are considered for training the Neuro-Fuzzy Controller. A Neuro-Fuzzy method that only relies on a limited amount of measured data for training purposes is also presented.

1. INTRODUCTION

Neuro-fuzzy controllers have previously been shown capable of capturing both high and low level characteristics of complex systems [9]. This is due to the fact that fuzzy sets allow systems to be described using high-level linguistic terms while back-propagation neural networks can capture the low-level characteristics of such systems. In this paper a Neuro-Fuzzy controller is used to perform adaptive channel reservation in micro-cellular networks where handover rates are expected to be high and non-Poissonian. Further, the Neuro-Fuzzy controller is able to adapt to the correct number of reserved channels when both the cell dwell time and call holding times have a general distribution. The applicability of this proposed approach is demonstrated for a micro-cellular mobile network with lognormal and gamma distributed call holding and cell dwell times.

The major advantage of adaptive channel reservation is its ability to change the number of reserved channels according to the dynamically changing traffic loads. Many variants of adaptive channel reservation have been proposed in the literature. Some schemes make use of channel state information in adjacent cells [14], others use direction and location prediction to adjust the amount of reserved bandwidth in cells [15][2]. All such schemes suffer from a major disadvantage wherein a large amount of information needs to be transported around the network in order to make reservation decisions. One solution that avoids the problem of excessive data transfer between cells is the use of local information at each based station. This information includes the new call arrival rate, the

handover arrival rate and the average channel holding time. Methods that make use of local cell information have been investigated in the literature, e.g. [12]. Most available studies dealing with adaptive bandwidth reservation assume that cell dwell times and call holding times are exponentially distributed. While this assumption holds when cell sizes are large, it has been shown both through analytical studies and measurements in mobile networks that this assumption is not accurate for micro-cellular mobile networks. Zonoozi *et al* [16] through the analysis of a mobility model have proposed a generalized gamma distribution for cell dwell times. Traffic studies have also shown that call holding times of current mobile networks follow a lognormal distribution [7]. The handover call arrival rate process is influenced by the cell dwell time distribution. It has been shown that if new call arrivals are poissonian and cell dwell times are exponentially distributed then the handover arrival process follows a Poissonian distribution [3]. If cell dwell times follow a general distribution then this will affect the handover rate process and the assumption that it is Poissonian does not hold any longer. To date very few studies have dealt with adapting the number of reserved channels when call handovers are not poissonian. In [10] the scheme is able to approximate non-poissonian conditions, however, the authors only consider Poisson arrivals and exponential cell dwell times. Non-exponential cell dwell times lead to high complexity in analyzing mobile networks.

Neuro-fuzzy controllers have the ability to deal with such complex problems. A Neuro-Fuzzy controller is a model free numerical estimator [9]. Neural networks make the fuzzy system more robust and assuming that representative data is available for training, they can optimize the fuzzy system to correctly match the training set [9]. When the Neuro-Fuzzy adaptive approach is applied to mobile networks, each cell can have an independent controller that will allow it to model its unique behavior based on the mobility and geographical characteristics of the cell. Hence correct quality of service constraints in terms of new call and handover probabilities can be maintained, while allowing better use of the available bandwidth under changing call load conditions.

Fuzzy logic has previously been applied to adaptive channel reservation for tuning the adaptation decision [8] where exponential cell dwell and call holding times were assumed. The approach taken in [8] is to choose the membership functions heuristically without using Neuro-Fuzzy techniques. Fuzzy logic has also been widely used for handover decision detection (in a signal level detector). In the latter case it is evident that the use of fuzzy logic provides a significant improvement in terms of correct handover detection [5]. Fuzzy logic has also been applied to multi-layer mobile networks for making decisions about which network layer a user should belong to based on fuzzy descriptions of speed and distance [13]. Fuzzy logic has also been shown to yield significant performance improvements in systems where the dynamics of the system are partially known and when there is unpredictability in the arrival conditions. For example, Bonde and Gizh [1] have shown how a fuzzy controller improves the utilization of an ATM buffer. More recently other works have appeared in the literature that use a Fuzzy inference engine. These include the work by Ma *et. al.* [17], where the authors present a heuristic design for a call admission controller. Shen *et. al.* [18] presents a call admission controller for a wide band CDMA cellular network. [18] uses the Fuzzy inference engine to make a bandwidth estimation of the incoming call. The work presented in this paper relies on a Neuro-Fuzzy admission controller which is shown to be applicable to more general distributions for the arrival and cell dwell times of an incoming call.

The work presented in this paper allows the adaptation of the correct amount of bandwidth that will guarantee a certain Grade of Service (GoS) in terms of call dropping probabilities for handover calls for mobile networks with non-exponential call holding and cell dwell times. While the fuzzy logic makes ‘soft’ decisions on the amount of bandwidth reserved, the neural net adapts the membership function parameters and the outputs of the fuzzy system. As long as the data set is a realistic representation of the cell behavior then the Neuro-Fuzzy controller will work correctly. In the method proposed in this paper, an initial training table is generated based on the analytical model of the micro-cellular mobile network with the exponential assumptions. The training table is then used to generate a Neuro-Fuzzy controller (NFC). The outputs of the Neuro-Fuzzy controller are then tuned by an ‘expert’, or through online data collection to account for non-exponential call holding and cell dwell times. A method is also presented that allows for the retraining of the NFC using a limited amount of measured data.

This paper is organized as follows: Section 2 discusses the details of the Neuro-Fuzzy logic controller (NFC) while Section 3 presents an analytical model of the micro-cellular network with bandwidth reservation based on the exponential assumptions for cell dwell times and call

holding times. Section 4 describes an algorithm that allows the application of the Neuro-Fuzzy controller when cell and call holding times are not exponential. Section 5 presents simulation results of the Neuro-Fuzzy controller for exponential and non-exponential models (lognormal and gamma distributions). Section 6 presents a method for training the NFC with a limited set of real data, while the conclusion is presented in Section 7.

2. ADAPTIVE CHANNEL RESERVATION USING A NEURO-FUZZY CONTROLLER

The structure of the proposed Neural-Fuzzy controller (NFC) is shown in Figure 1. The NFC takes two inputs, the new call rate λ_n and handover call rate λ_h . The output y is the number of channels to reserve while z is used in the training phase to feed back to the NFC the correct output.

The NFC consists of 5 layers. Layer 1 consists of the input nodes that pass on the inputs to layer 2. Layer 2 nodes perform a fuzzification function [9]. The new and handover call rates are described by the following linguistic variables (membership functions): *Low*, *Moderate* and *High* input rates. There are six nodes in this layer; each three nodes represent the 3 member functions for each input. The fuzzification function used is a general bell curve and is defined by:

$$f_i(u_{ij}) = \frac{1}{1 + \left| \frac{u_{ij} - c_{jn}}{a_{jn}} \right|^{2b_{jn}}} \quad (1)$$

where u_{ij} is the input, c_{jn} is the center of the generalized bell curve and a_{jn} and b_{jn} are the slope parameters. This particular function was chosen because it combines the smooth slope of a bell curve with increased variance (a stretched out bell curve), hence reducing the required number of membership functions (if the bell curve alone was used). Reducing the number of membership functions significantly reduces the number of fuzzy rules resulting in faster convergence in training. It was determined through simulation that 3 membership functions were a good compromise for the NFC. It was found that if only 2 functions are used per input (*Low* and *High*), the NFC does not converge to the required output. Using 4 or more membership functions per input resulted in slower training times as well as local minima and maxima in the output surface. It was observed that these (local maxima and minima) are due to incomplete training data (small data set). Using 3 membership functions resulted in an accurate representation of the data set, as well as avoiding the problems that resulted from choosing a larger number of membership functions.

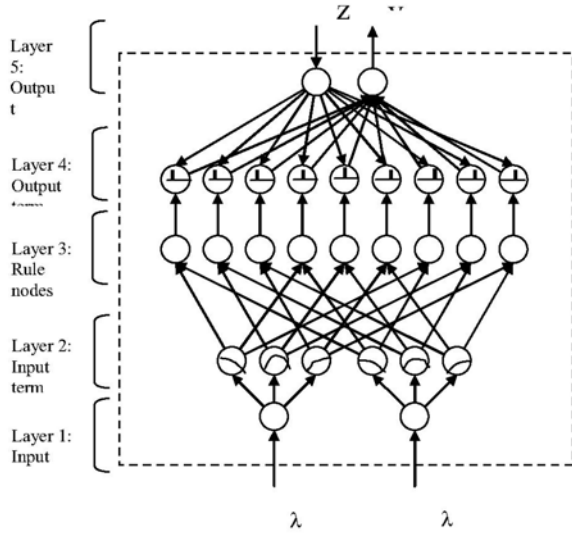


Figure 1. Neuro-Fuzzy Controller Structure.

3. CELLULAR NETWORK MODEL

A uniform mobile network is considered as shown in Figure 2. Mobile terminals have an equal probability of handing over in all directions. All the cells are of equal size and each one has a total capacity of N channels (units of bandwidth). New calls have access to $(N-h)$ channels, while handover calls have access to all N channels. If cell dwell times are assumed to be exponential, then the arrival rate of handover calls is Poissonian [3]. Hence in this case

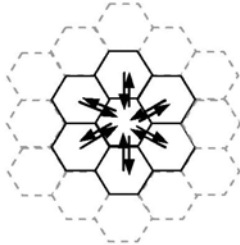


Figure 2. A uniform mobile network.

an analytical model can be used to solve for the new and handover blocking probabilities.

Let ρ_H be the handover load into each cell given by:

$$\rho_H = \frac{\lambda_H}{\mu} \quad (2)$$

and let the total load be given by:

$$\rho_T = \frac{(\lambda_N + \lambda_H)}{\mu} \quad (3)$$

where $1/\mu$ is the mean channel holding time and it is a combination of the mean cell dwell time as well as the mean call holding time. Using a Markov model, the resulting handover call blocking probability and the new

call blocking probability are determined by equations 4 and 5 respectively:

$$P_{hb} = \frac{\left(\frac{\rho_H^h \cdot \rho_T^{(N-h)}}{N!} \right)}{G} \quad (4)$$

$$P_{nb} = \frac{\left(\frac{\rho_T^{(N-h)}}{(N-h)!} + \rho_T^{(N-h)} \cdot \sum_{m=N-h+1}^N \frac{\rho_H^{m-(N-h)}}{m!} \right)}{G} \quad (5)$$

where

$$G = \sum_{n=0}^{N-h} \frac{\rho_T^n}{n!} + \rho_T^{(N-h)} \cdot \sum_{m=N-h+1}^N \frac{\rho_H^{m-(N-h)}}{m!} \quad (6)$$

4. NON-EXPONENTIAL TRAINING OF THE NFC

As noted earlier, the NFC can model the underlying characteristics of a system. For the case of adaptive channel reservation, it is the number of channels to reserve for a given new and handover call rates that will result in a certain handover blocking probability.

Simulation experiments presented later on in Section 5 indicate that an initial training set could be generated based on the exponential model and after several adjustments to the outputs of the NFC, the correct output for non-exponential models can be obtained. New call arrivals are initially assumed to be Poissonian. The first step in obtaining the equivalent exponential model is to find the relationship between the handover rates for the exponential and non-exponential cases (this is demonstrated in Section 5 for the case of a lognormal cell dwell time). The NFC is then trained with this initial data set and an initial controller is generated. The outputs (but not the membership functions) of the controller are finally tuned until the correct number of channels that result in obtaining the correct handover blocking probability (which in all our simulations is assumed to be 0.002) are reserved. This process is represented graphically in Figure 3 (The detailed process of making the adjustments is presented in Figure 9).

5. SIMULATION RESULTS

Simulations were conducted over a ring network (of 20 identical cells) with mobile units having an equal probability of handing over in two directions. The mean cell dwell time was chosen to be 30 seconds and the mean call holding time was chosen to be 100 seconds. These values model a micro-cellular mobile network with a high handover rate. The NFC was initially tested against an exact exponential model as described in Section 3. The NFC was then trained to adapt to lognormal cell dwell times and exponential call holding times (Section 5.1).

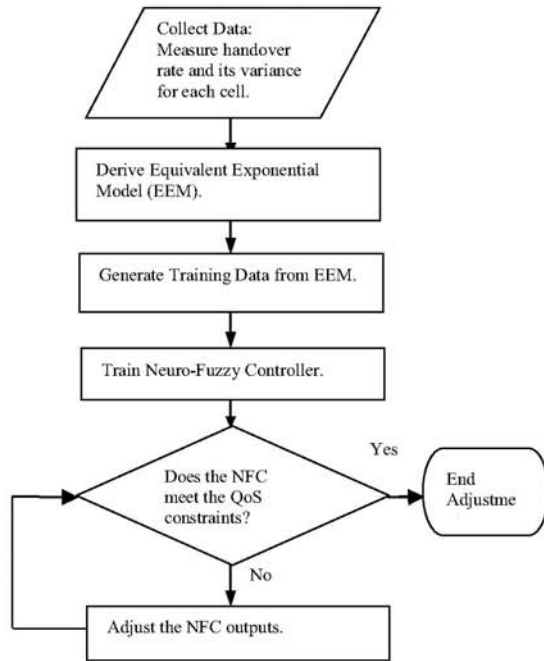


Figure 3. The Design Process of the NFC.

5.1 Testing the NFC against the Exponential Model

The analytical model of Section 3 was used to generate a training data set that was subsequently used to train the NFC. The trained NFC was then used in a mobile network simulation and the results were compared to those obtained from the exact model. A training table was generated for the NFC using Equation 5. The table consists of two inputs and one output. The inputs are the new call rate and the handover call rate, while the output is the number of reserved channels that result in a handover blocking probability equal to or less than 0.002. Figures 4(a) and 4(b) show the membership functions of the new call rate before and after training respectively. The corresponding membership functions for the handover rate are shown in Figure 5(a) and 5(b).

The initial membership functions were chosen to cover the desired range of inputs but it is clear that after training, the membership functions have shifted as they converged towards the training data. This is particularly evident in Figure 5(b). The output surface of the NFC is shown in Figure 6. The figure shows the number of channels that should be reserved for a particular set of inputs. The error in convergence could also be seen, as the surface dips below zero. This was corrected by setting any output below zero as equal to zero. Figure 7 shows that the NFC is able to mimic the analytical model and correctly perform the task of adapting the number of reserved channels that result in the desired grade of service.

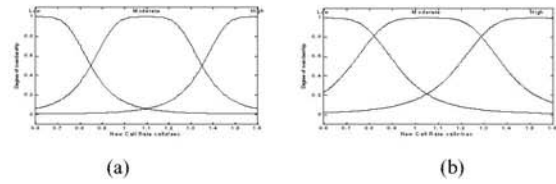


Figure 4. Fuzzy Membership Functions: "New Call" Rate Before (a) and after (b) Training.

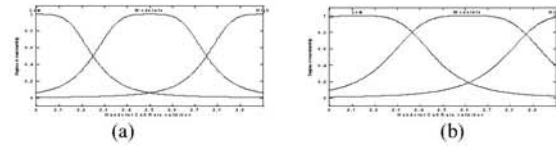


Figure 5. Fuzzy Membership Functions for "Handover Call" Rate Before (a) and after (b) Training.

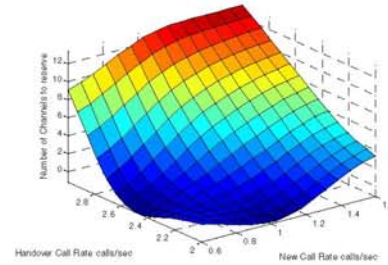


Figure 6. The Neuro-Fuzzy Output Surface over all the Range of New and Handover Call Rates.

5.2 Applying the NFC to Lognormal Cell Dwell Times

The cell dwell time was modified to reflect a more realistic network situation where the cell dwell time distribution is no longer exponential. The variance of the cell dwell time distribution may depend on the geographical features of the cell as well as on the user mobility distribution. For this case study a lognormal distribution was chosen as an example of a non-exponential distribution. This distribution was applied to cell dwell times so that the resulting call handover process was no longer Poissonian. A mean cell dwell time of 30 seconds and a squared coefficient of variation of 3 were used. The value for the squared coefficient of variation is not critical and values less than 1 can be used as well since the cell dwell time has also been suggested to follow a gamma distribution [4].

By using the simulation with lognormal cell dwell times the handover rates into the cells were measured and compared to the values obtained when using the exponential model of Section 3. It was found that a near linear relationship existed between the constant relating the two handover rates and the squared coefficient of variation of lognormal cell dwell times as shown in Figure 8.

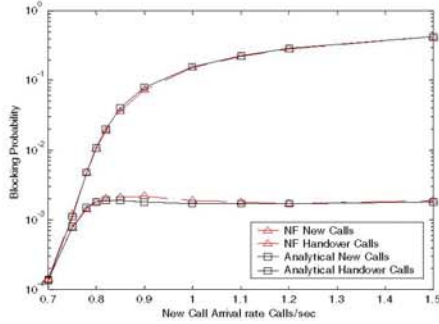


Figure 7. Call Blocking Performance for New and Handover Calls.

Hence, by measuring the variance of the cell dwell times, the squared coefficient of variation of cell dwell times can be readily determined and this can be subsequently used to get the equivalent Poissonian rate from the following equation

$$\lambda_{hPos} = \left(\frac{1}{\alpha}\right)\lambda_{hLog} \quad (7)$$

where λ_{hLog} is the measured handover rate for the case of lognormal cell dwell times and λ_{hPos} is the equivalent Poissonian handover rate. Having obtained the equivalent Poissonian rate, the analytical model of Section 3 can then be used to generate a new data set. This data set is then used to generate the new fuzzy model. It is then possible to adjust the output of the resulting model (so that its outputs result in the correct grade of service) in one of two ways,

- By heuristically adjusting the outputs of the fuzzy system.
- By collecting more data online and modifying the training table, the retraining the NFC with the new data set (Section 6).

Manual adjustments to the outputs in Layer 4 (*Output1*, ..., *Output9*) are made iteratively until the handover call blocking requirements are met. This is not a long process and it is possible to get an accurate result after the first or second iteration. This is made possible by the inherent characteristics of fuzzy logic, where upon by making one adjustment, all other outputs in the relative region of the output surface are adjusted in proportion to the membership functions. The first step is to modify the *most significant output*, this is the output (in Layer 4) that is having the most impact on the overall output result (for a particular set of inputs). The second adjustment is made to the *next significant output value*, and so on until the required output values (that result in the correct grade of service) are reached. One possible way of making such adjustments is shown below in Figure 9. It is possible to over-adjust the outputs. This is avoided by checking all the outputs after every adjustment.

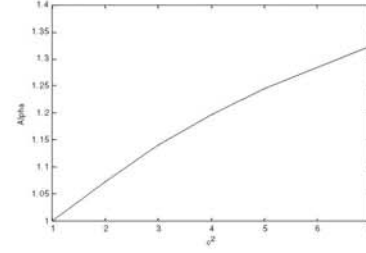


Figure 8. Relationship between α and c^2 .

The results of the simulation are depicted in Figure 10 and show the blocking performance of NFC-based bandwidth reservation before and after output adjustment. Figure 10 also shows that the NFC outperforms fixed bandwidth reservation (FR3, where 3 channels were reserved) as well as Distributed Connection Admission Control (DCAC) proposed in [10] which uses the number of ongoing calls in adjacent cells to make admission decisions.

Figure 11 shows the relative cost of the above four bandwidth reservation schemes. The relative cost combines the two blocking probabilities into a single function and penalizes the dropping of handover calls by considering them to be some multiple of new calls. In the literature this value is usually set to 10 although much higher numbers have also been used [6]. Hence in our case dropping one handover call is considered equivalent to blocking 10 new calls. Equation 8 was used to calculate the relative cost as follows:

$$C = \frac{n_n + 10 * n_h}{n_t} \quad (8)$$

where n_n , n_h and n_t are the number of new calls, number of handover calls and total number of calls blocked or dropped, respectively.

6. ONLINE TRAINING

The above algorithm used manual adjustments of the NFC output to fine tune the controller. In this section, an algorithm is investigated online results are re-entered into the training set to correct for any errors in the fuzzy admission controller. These online results could be obtained after running the NFC in the field.

The method that is presented in this section assumes that one can collect enough 'real' points and add them to the training table to retrain the fuzzy logic admission controller. In fact such an assumption is not realistic in a real system, where the network operator dimensions the bandwidth in order to avoid the edge conditions or in other words where blocking of new and handover calls is most likely to occur. It is much more likely that only few instances of the edge conditions will be available to the network operator.

In this algorithm, it is assumed that only very few points are available to the network operator to retrain the fuzzy logic admission controller. These few edge conditions are extrapolated by the algorithm in order to generate more data points. We refer to these points as pseudo

measurements. This is done to highlight the fact that they are not real measurements, but approximations extrapolated from very few real measurements. The main assumption made by this algorithm is that the function that it is trying to adapt to is monotonic for small distances around these measured points. In the case of the blocking probability that is clearly the case.

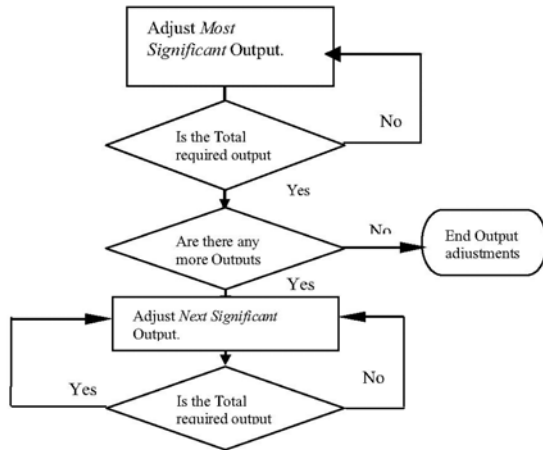


Figure 9. Output Adjustment Process.

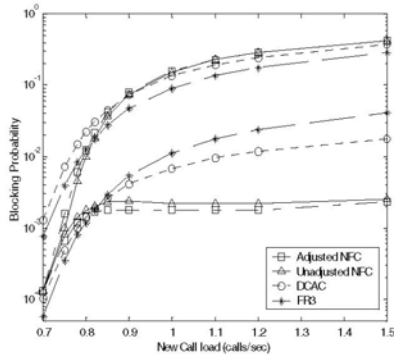


Figure 10. Blocking Performance of Different Reservation strategies.

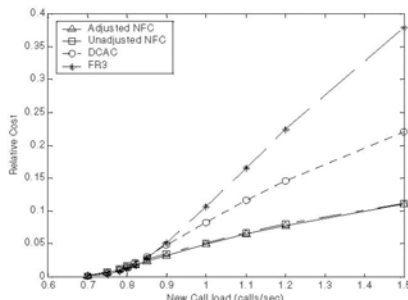


Figure 11. Cost Function of Various Bandwidth Reservation Schemes.

The algorithm works by adjusting the training set of the particular point of concern as well as the surrounding points. If only the single point is actually used it will be

drowned out by all other points. If the same point is replicated many times in the training set, it may result in simply causing that particular section of the admission controller to retrain and will not affect other areas which may be in error. This is more evident if many membership functions are used to represent the data set.

6.1 The algorithm

Repeat steps 1 and 2 until all points are within the acceptable value for the handover blocking probability.

Step 1: For the entire range of operating points calculate the error between the simulated outputs and desired outputs for both new and handover call blocking probabilities. In this case the output that is being controlled is the handover blocking probability. (This is the same step as the previous algorithm).

Step 2: For the input range as specified around the measured point adjust the original training set by applying the retraining function.

For example the training range around a specific measured point could be $\pm 5\%$ for all inputs. Hence all points within this range will be modified by the retraining function. The retraining function specifies the magnitude of how the change will occur. For example three possible training functions that could be applied are flat, descending gradient or bell shape. In the case of a flat function, the specific points that were chosen for retraining will simply apply an equal adjustment to the entire set of points in the range of values. For example if the original training set specified that 10 channels should be reserved for a specific set of inputs, but the measured data indicated that 8 is a better fit, then all points within the retraining range will have their values shifted down by 2.

If the gradient method is chosen, then the points of the training set will be adjusted in proportion to how far they lay away from the measure point. The closer the training data point is to the measured one the more adjustment that takes place. The further away it is, the less adjustment takes place. This is the same for a bell type function that will slowly decay away from the measured point.

6.2 Results

Figure 12 below shows the new and handover call blocking probabilities for the new retraining algorithm as well as the original and the membership function changing algorithm presented in the previous section. The figure shows that the measured or 'real' points (in this case 3) that had been outside the allowable range had been brought back in within the tolerance limit for the handover blocking probability. Hence, the fuzzy logic admission controller has been retrained to reflect the measured data, but in this case only relying on 3 measured points from the 'real' system (which is the simulated system in this case).

The flat and the simplest retraining functions were used in this case. Only one pass was made through the data as the adjustments that needed to be made are small, and the granularity of the single channel does not allow further refinement.

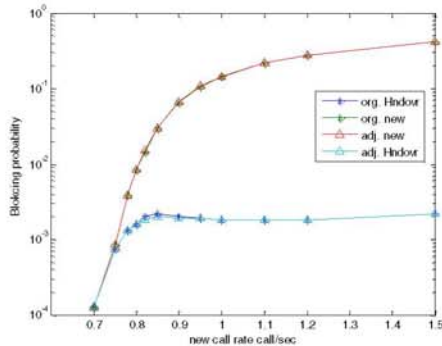


Figure 12. New and Handover blocking probability without error bars for the original admission controller and the two adjustment algorithms.

Figure 13 shows the difference between the original and retrained surfaces of the fuzzy logic admission controller. It is clear that the surface has been adjusted appropriately to reflect the new data. It seems that adjustments to the training data at least in this case maybe more beneficial as this results in a smooth adjustment of all the admission decisions.

The conclusion can be drawn that one can successfully correct for the original training performed using the approximate poissonian model when actual results differ from the desired outputs. This difference is due to the fact the actual system has difference characteristics in terms of arrival rates, call holding time and sell dwell times. These simulation results show that it is quite possible to readily automate the adjustment algorithm to correct for any errors and two possible implementations of the algorithm show some promising results.

7. CONCLUSION

A Neuro-Fuzzy controller was developed to carry out adaptive channel reservation in micro-cellular networks with general cell dwell times and call holding times. To date the analysis of micro-cellular networks reported in the literature has been restricted to the use of exponential call holding and cell dwell times for tractability reasons. The results presented in this chapter showed that the NFC outperforms both DCAC and fixed bandwidth reservation. Two algorithms for designing and training the NFC were also presented. These algorithms were used and tested through simulation in two case studies; One dealing with lognormal cell dwell times and the second with lognormal call holding and gamma cell dwell times. The results showed that the NFC was able to meet the required GoS constraints after one or two adjustments, making the proposed method a practical solution to the problem of improving bandwidth utilization whilst reducing the

possibility of a degraded user experience through call drop-outs in mobile networks with a small cell size.

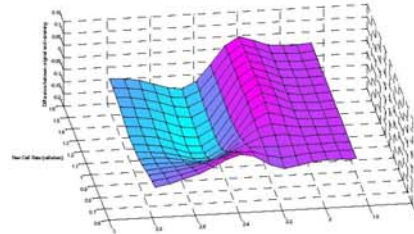


Figure 13. Difference between output surfaces for Fuzzy Logic admission Controller between original and 2nd algorithm (another view).

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