CHAPTER 6

ADAPTIVE NEURO-FUZZY LOGIC BASED LOCATION MANAGEMENT

In this chapter, the application of a Location based Management for mobile networks based on Adaptive Neuro-Fuzzy Inference System (ANFIS) for reducing the location update cost is presented. A class of adaptive network, which are functionally equivalent to fuzzy logic control, is referred to as Adaptive-Network Based Fuzzy Logic controller also known as Fuzzy Neural Network (FNN). In this thesis, Adaptive-Network Based Fuzzy logic structure [56, 46] and fuzzy rules [43] is employed to design an Adaptive Neuro-Fuzzy Logic Based Location Management System for reducing the location update cost.

The key factors that distinguish Adaptive Neuro-Fuzzy Logic Based Location Management System from other systems are

- The system deals the non-linearity of the system in a better way.
- The decision rules are framed from training examples. This avoids the need of an operator’s experience about the system.
- The system is adaptive: (i.e.) the parameters of the fuzzy set are tuned automatically.
- The system can generalize: they can correctly process data that broadly resembles the data trained originally.
- The system incorporates expert’s knowledge if necessary. This shows its transparency, which is a disadvantage of normal feed forward multilayer network due to its black box characteristic.
- The ANFIS based system requires less computational time compared with Artificial Neural Network based systems.
6.1 ADAPTIVE NEURO-FUZZY BASED LOCATION MANAGEMENT

The Adaptive Neural Network Based Fuzzy Logic based Location Management system is designed with two inputs, the day of the week ($D_i$) and the time in that day ($T_i$), and output Cell Identity and their probability of presence of the user in that Cell Id. The training data is viewed to be very complex hence seven linguistic variables for each input variable were used to get the desired performance. The linguistic variables are specified by Gaussian membership functions and as a result 49 rules are devised. The rule base contains the fuzzy IF-THEN rules of sugeno's first order type in which the output of each rule is a linear combination of input variables plus a constant term [56, 46].

IF $D_i$ is $A_j$ AND $T_i$ is $B_j$ THEN

$$C_{id} = p_i D_i + q_i T_i + r_i$$

$$prob \_user = u_i D_i + v_i T_i + z_i$$

The universe of discourse for both the input variables is normalized and the gain parameters chosen based on input-output space are $D_i$ gain=1.0, $T_i$ gain=1.0, output gain=0.01

The architecture of the ANFIS based Location Management showing $D_i$ and $T_i$ is shown in Figure 6.1 where node functions in each layer are as described below.

Layer 1:

Each node in this layer performs a Gaussian membership function.

$$O_{i,j} = \mu_{A_j}(x_i) = \exp \left(\frac{(x_i - c_{ij})^2}{\sigma_j^2} \right) \quad i = 1, 2 \; \& \; j = 1, \ldots, 7 \quad (6.1)$$
Where $c_j$ and $\sigma_j$ are the center and width of the $j^{th}$ fuzzy set $A_j$ respectively, $x_i$ is the input to the node $i\ (D_i, T_i)$.

**Figure 6.1 Architecture of ANFIS based Location Management System**

*Layer 2:*

Every node in this layer represents the fixing strength of the rule.

$$O_{2,i} = w_i = \min(\mu_{A_i}(D_i), \mu_{B_i}(T_i)) \quad i = 1, \ldots, 7$$

(6.2)

Eventually the nodes of this layer perform fuzzy AND operation.

*Layers 3:*

The nodes of this layer calculate the normalized firing strength of each rule. The layers 2 & 3 are merged in the implementation stage.
\[ O_{3,j} = \frac{w_j}{\sum w_i} = \frac{w_j}{w_j} = 1, \ldots, 49. \] (6.3)

- \( w_j \) – firing strength of a rule.

**Layer 4:**

The nodes in this layer output the weighted consequent part of the rule table.

\[
O_{4,i} = w_i f_i = w_i (p_i D_i + q_i T_i + r_i) \quad i = 1, \ldots, 49. \] (6.4a)

\[
O_{4,i} = w_i f_i = w_i (u_i D_i + v_i T_i + z_i) \quad i = 1, \ldots, 49. \] (6.4b)

where \( \{p_i, q_i, r_i\} \) and \( \{u_i, v_i, z_i\} \) are the parameter set of this node for Cell Id network and Probability outputs respectively.

**Layer 5:**

The single node in this layer computes the overall output as the summation of all the incoming signals.

\[
O_{5,i} = \sum w_i f_i \quad i = 1, \ldots, 49. \] (6.5)

where, \( O_{5,j} \) denote the output in layer 5.

**6.2 TRAINING THE ANFIS BASED LM SYSTEM**

The ANFIS based Location Management System is trained in such a way that there is no expert available and the initial values of the membership functions parameters are equally distributed along the universe of discourse and all consequent parts of the rule table set to zero. The scheduler starts from zero output and during training it learns the rules and functions. Thus during
training the network structure update MF and rule base parameters according to the gradient descent update procedure.

**Figure 6.2 Membership function of Input Variable Di(Day)**

**Figure 6.3 Membership function of Input Variable Ti(Time)**

The Location Management system was trained by data’s created from users profile in various conditions. The training was performed over a wide range of operating situations. A total of 1500 input-output data pairs are
created for the training of Neuro fuzzy based scheduler. The MF for the input variables $D_i(Day)$ and $T_i(Time)$ are shown in Figure 6.2 and Figure 6.3.

The ANFIS representation with input and output variables for predicting the Cell Id and its Probability are shown in Figure 6.4 & 6.5.

**Figure 6.4 ANFIS Mapping for Prediction of Cell Id**

A sugeno type neuro fuzzy system is used to train the system and the type of membership function used for input $D_i$ is Gaussian. The number of membership function used for input $D_i$ is 7. The type of membership function used for output $T_i$ is Gaussian and the number of membership function used for output $T_i$ is 7.
Figure 6.5 ANFIS Mapping for Prediction of Cell Id and Probability

6.3 SIMULATION STUDIES

To assess the accuracy of the presented analytical model, in this section a performance evaluation of the Location Management System as well as a detailed model, which captures all relevant aspects of our approach in a concise way is presented. The simulation models both the call delivery and mobility behavior of users offering the ability to consider different service types and different MT groups over a range of cell-layout scenarios. Three different cell layout scenarios have been investigated. The first assumes macrocells only (9 Km²), the second medium-size cells (1 Km²), while the third small-size microcells (0.1 Km²).

In our experiments, 1,000 MTs are simulated and we generated 1,000 samples for each cell layout scenario assuming normal distributions using the statistics estimated from the real data. We run simulations for the probability of a user being roaming within his associated list from 0.5 to 0.99. We assume
that a user is within that area covered by its list at least half of time. In practice, it would not be for a performer to have a list of likely positions in which a user is not found at least half of the time. In the case of users whose position at a given moment is unpredictable and the past knowledge of their location cannot predict their future location, our strategy is not applicable.

Finally, when the size of an LSTP is large because of the scattered location of mobile users, we can estimate that the probability of a user moving under the coverage of such an area is high; on the other hand, if the LSTP covers a small area, the user is likely to have his probable location areas among several LSTPs.

**Voice model:** A stochastic process can describe the voice traffic model, with arrival times corresponding to the beginning times of sessions. The call arrival process is assumed to be Poissonian, while the call duration is exponentially distributed (Quintero et al., 2004) [5]. The call arrival rate (calls/MT/hour) is 3. Each session describes a complete phone call and contains an ON-OFF period. ON periods occur when voice is generated, whereas no voice is generated during OFF periods. The ON period distribution follows an exponential law with mean 352 ms and the OFF period also follows an exponential law with mean 650 ms. Within the ON period, voice arrives at a fixed rate $1/r$. Therefore, $1/r$ is the sampling rate. The call mean time duration is 5 min. The exponential distribution has the following probability density function: $f_{VOLP}(x) = \lambda e^{-\lambda x}, x \geq 0$, where $A = (300x)^{-1}$, $x$ represents the time.

**Mobility model:** In this research, the MTs are assumed to be moving at the same velocity $V$ and their direction movement is uniformly distributed over $[0, 2\pi]$. The average number of LA crossing, $C$, of a zone of perimeter $P$ is given by $C = \rho PV / \pi$, where $\rho$ is the users density in the LA. To perform this evaluation, we define four classes of users depending on their velocity and the
cell radius in which they are roaming Markoulidakis et al., (1998) [58]. These categories are:

- users located in buildings,
- pedestrians with a speed following the Gaussian distribution with mean value 4 km/hr and variance 30 percent,
- car passengers with a speed following the Gaussian distribution with mean value 15 km/hr and variance 30 percent, and
- car passengers with a speed following the Gaussian distribution with mean value 40 km/hr and variance 30 percent.

Finally, we assume that a LA is a square of 5 x 5 cells and we consider a network that contains 30 LAs. We set the density p to 1,000 users per cell. We now examine the impact of location management procedures on the database. In order to estimate the database loads on the VLR due to the location search procedure, we add the database access generated by both originating and terminating calls. Similarly, in order to evaluate the VLR and HLR databases load due to the location update procedure, we add the database access generated by both registration and the registration cancellation operations.

The several parameters that will be used for the different simulation scenarios are:

- K is the probability that a MT will be found roaming under one of its likely areas as registered in the profile of a given LSTP (as an average). It will be close to 1 for deterministic users and will vary between 0.5 and 0.8 for quasi-deterministic users. Random users cannot be assigned a list and, thus, their values are below 0.5, n is the average number of tries needed to page a MT from the ILD where it is roaming in. Its value depends on the probability distribution of the user among the areas in the list and the size of the list itself.
Uniform, linear, and exponential models are discussed in Pollini et al., (1997) [63]. For each of them, an average value of \( n \) is given as a function of the size of the list, \( k \) is the number of location data tables that must be updated each time the MT changes LSTP. \( k \) normally ranges from 4 to 12. If its value is 0, it indicates that no replication (i.e., location data tables) is used. CMR is the independent variable in the simulations as in Chen et al., (2003) [15]. All users are classified according to their call-to-mobility ratio (CMR), where \( \text{CMR} = \frac{\lambda}{\mu} \), \( \lambda \) is the average number of calls to a target MT per time unit, while \( \mu \) is the average number of times the user changes LA per time unit. The value of +the CMR varies from 1 to 10.

A LSTP consists of \(< x \times x > \) LAs arranged in a square and each LA is itself a square. Furthermore, LAs are composed of RAs, which are sets of hexagonal cells. We assume that the MTs are uniformly distributed within an LSTP area and each MT exhibits the same arrival call rate at every MSC/VLR. When a MT leaves a LA, each of the four sides has equal probability.

### 6.4 Deterministic Users (\( k > 0.8 \))

This section deals with the users for which the profile collects a great part of their daily routines. These users are called "deterministic" users. Figure 6.6 shows the results for a simulation of the scheme, where we vary the configuration of the pointers’ system. We varied the pair \((k, \nu)\) from \((0, 0)\) to \((12, 0.9)\). When \( k \) and \( \nu \) both equal 0, there are no pointers. These two parameters where then increased up to 12 and 0.9, respectively, meaning that there are 12 pointers to update for an average user and a 90 percent chance of finding a distant pointer for that user when the system pages her. In this configuration, link costs dominate network costs.
(a) Relative cost to standard UMTS

(b) Relative cost to Cayrici’s strategy

Figure 6.6 Relative Cost for Deterministic User K=0.9 with FNN
Table 6.1 Relative cost for Deterministic User K=0.9 with FNN

<table>
<thead>
<tr>
<th>CMR</th>
<th>Relative cost with Cayirci’s strategy</th>
<th>Relative cost with UMTS Procedure</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.4352</td>
<td>0.6065</td>
</tr>
<tr>
<td>2</td>
<td>0.4857</td>
<td>0.7648</td>
</tr>
<tr>
<td>3</td>
<td>0.5148</td>
<td>0.8757</td>
</tr>
<tr>
<td>4</td>
<td>0.5336</td>
<td>0.9579</td>
</tr>
<tr>
<td>5</td>
<td>0.5469</td>
<td>1.0211</td>
</tr>
</tbody>
</table>

Table 6.1 shows the relative cost of UMTS and Cayirci with FNN algorithm for K value of 0.9. From the table it’s clearly evident that for both the strategies the proposed algorithm performs better and reduces the overall signaling cost. Table 6.2 shows the total cost of the three strategies.

Table 6.2 Total cost for Deterministic User K=0.9 using FNN

<table>
<thead>
<tr>
<th>CMR</th>
<th>Total cost of Cayirci’s strategy</th>
<th>Total cost of UMTS Procedure</th>
<th>Total Cost of FNN based LM</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>118.71</td>
<td>88.07</td>
<td>53.41</td>
</tr>
<tr>
<td>2</td>
<td>163.49</td>
<td>106.79</td>
<td>81.67</td>
</tr>
<tr>
<td>3</td>
<td>208.29</td>
<td>125.50</td>
<td>109.90</td>
</tr>
<tr>
<td>4</td>
<td>253.06</td>
<td>144.22</td>
<td>138.14</td>
</tr>
<tr>
<td>5</td>
<td>297.88</td>
<td>168.94</td>
<td>166.37</td>
</tr>
</tbody>
</table>
When the number of pointers increases, the signaling cost is significantly reduced in comparison with the cost obtained for the UMTS standard. For the (12, 0.9) pair, the relative cost ranges from 10 percent for low CMRs to 40 percent for high CMRs. This means that pointers do achieve a substantial reduction in the overall signaling cost, even if they increase the location update cost. For each configuration, we observe that, when the location search cost dominates, the cost of our scheme increases as CMR values increase. This was to be expected since user pattern learning strategies tend to reduce location update costs at the expense of higher paging costs. However, pointers help us minimize this increase.

In Figure 6.6a, we observe the same trend as seen in Figure 6.6b. In other words, pointers are effective in reducing the global cost of a location update. In this case, where the location search dominates, the relative cost decreases along with CMR values, down to around 55 percent of the cost obtained for Cayirci’s algorithm. When location updates dominate (i.e., low CMRs), our scheme produces a worst cost because we use a pointer system that does not exist in Cayirci’s algorithm. When considering deterministic users that have a 99 percent probability of roaming within their profile, Cayirci’s algorithm achieves a very low cost compared to our scheme. This difference can be explained by the fact that our scheme has to register other location information, especially when changing the user changes LSTPs.

When the user is slightly less deterministic (i.e., a probability around 90 percent of roaming according to its profile), the location update costs for both schemes get closer and the location search procedure decides which algorithm has a smaller cost. In situations where pointers are likely to be used, our scheme always outperforms Cayirci’s and the cost reduction is always higher than or equal to 40 percent. If our scheme were not to use the pointers system, Cayirci’s strategy would always have a better performance. In this specific case, the cost of our scheme increases since it would need additional updates.
when an MT makes an inter-LSTP movement, even when this move is within the profile (Figure 6.6b).

6.5 QUASI-DETERMINISTIC USERS (0.8 > K > 0.5)

Figure 6.7a shows how the number of paging trials increases the cost of our scheme when compared to the UMTS standard where the user's location is always explicitly known. However, the proposed algorithm outperforms the UMTS standard for every CMR between 1 and 10 and for a value of n lower than 4. When n reaches 4, the cost of our scheme is higher than the cost for the UMTS standard for high values of CMRs (i.e., location search takes more importance). Nevertheless, for every paging trial that is not completed (from 3 to 2, 2 to 1, etc.), our scheme has a 42 percent cost reduction when compared to the UMTS standard.

Using the same simulation parameters, but with Cayirci's strategy, yields the results shown in Fig. 6.7b. With a quasi-deterministic user, our strategy always outperforms Cayirci's in the studied range of CMRs because we use the locality property and a pointer system. We can see that the cost reduction is even more important for low values of n (i.e., less paging trials) and low CMRs (i.e., location update dominates). The voice paging trials, in our strategy, are less expensive than in Cayirci’s since they are performed from the LSTPs. Moreover, Cayirci's strategy necessitates expensive location updates whenever the user roams out of the profile. Our scheme reduces the cost in those situations. The relative cost ranges from 50 percent to 60 percent for an intermediate number of paging trials n.
Figure 6.7 Relative Cost for Quasi Deterministic User K=0.7 with FNN
Table 6.3 Relative cost for Quasi Deterministic User K=0.7 with FNN

<table>
<thead>
<tr>
<th>CMR</th>
<th>Relative cost with Cayirci’s strategy</th>
<th>Relative cost with UMTS Procedure</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.4200</td>
<td>0.5718</td>
</tr>
<tr>
<td>2</td>
<td>0.4553</td>
<td>0.6926</td>
</tr>
<tr>
<td>3</td>
<td>0.4759</td>
<td>0.7774</td>
</tr>
<tr>
<td>4</td>
<td>0.48951</td>
<td>0.8401</td>
</tr>
<tr>
<td>5</td>
<td>0.4990</td>
<td>0.8884</td>
</tr>
</tbody>
</table>

Table 6.4 Total cost for Quasi Deterministic User K=0.7 with FNN

<table>
<thead>
<tr>
<th>CMR</th>
<th>Total cost of Cayirci’s strategy</th>
<th>Total cost of UMTS Procedure</th>
<th>Total Cost of FNN based LM</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>115.87</td>
<td>88.07</td>
<td>50.35</td>
</tr>
<tr>
<td>2</td>
<td>157.80</td>
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<td>73.96</td>
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<td>3</td>
<td>199.74</td>
<td>125.50</td>
<td>97.56</td>
</tr>
<tr>
<td>4</td>
<td>241.67</td>
<td>144.22</td>
<td>121.15</td>
</tr>
<tr>
<td>5</td>
<td>283.60</td>
<td>168.94</td>
<td>144.75</td>
</tr>
</tbody>
</table>

Table 6.3 shows the relative cost of UMTS and Cayirci with FNN algorithm for K value of 0.7. The total cost comparison with FNN, UMTS standard and Cayirci’s standard is shown in Table 6.4. When compared with the ANN and CCNN approaches the proposed method using FNN has proved to be more efficient.