Predicting Wireless Coverage Maps Using Radial Basis Networks

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***Abstract*— Accurate assessment of the wireless coverage of a station is a critical step toward deploying more base stations in Ultra Dense Networks, and it is considered as one of the key features of the 5G networks. Quickly and efficiently determining the reception coverage of transmitters becomes a complicated problem when interfering transmitters are introduced to the scenario. It becomes increasingly more complicated when the transmission powers of those transmitters are not uniform. Artificial Neural Networks are the most suitable learning algorithms for recognizing and predicting non-linear patterns. In particular, a Radial Basis Network is a type of Artificial Neural Network which typically uses a Gaussian kernel as an activator as opposed to a sigmoid function. In this paper, we suggest using Radial Basis networks in order to predict coverage maps. We show how it is possible to train the Radial Basis Network to generate coverage maps based on samples and we check the accuracy level of the learning process on a test set. Using Radial Basis Network can improve the cellular coverage prediction and therefore it can enable a more efficient spectrum allocation.**

Keywords—Coverage maps; Machine Learning; Radial Basis Networks; SIR

I. Introduction

Wireless communication systems have become an integral part of our society. Without them, we would lack the convenient mobility that we take for granted. The two most important features of wireless communication systems are the distance over which they can perform and the data rate they can offer. These features often have tradeoffs between each other. Normally faster data rates are preferable, however attempting to improve these rates may limit the range of the transmitters in the network due to a higher Signal to Interference Ratio (SIR) required Alternatively increased throughput can be reached thanks to larger bandwidth but will reduce the number of channels available. Fewer channels mean poor frequency reuse and therefore minimizes the capacity of the network. Increasing the distance over which a cell operates has a similar effect as well. It also reduces the frequency reuse and ultimately the capacity of the network. Having smaller cells does not always solve the problem since there are numerous issues involved such as network complexity, co-channel interference and hand-offs. Therefore, a great amount of effort has been put into researching methods of optimizing these tradeoffs. Finding the optimum balance in some of these issues can increase the much needed network capacity as well as its effective range.

Presently, the mobile communications industry strives to find more efficient and effective algorithms that handle user equipment (UE) uplink power levels and determine when to cause inter-cell hand overs (HO). It is important to regulate a UE's transmission power in order to ensure that the UE does not cause unnecessary interference to other UEs operating on the same frequency. This is generally an issue in CDMA systems as well as in every other cellular system, especially when a UE experiences interference near its base station (BS) [1]. In such cases, the UE causes interference to the uplink channels of other UEs in the same cell, since it must transmit at a high power level in order to communicate with its BS. Moreover, the algorithms, which determine whether to generate an HO, are also important to cellular networks, since poorly decided HO criteria can create coverage holes and instability in the network [2]. In addition, accurate assessment of the wireless coverage of a station is a critical step toward deploying more and more base stations and even more relevant with the advent of Ultra Dense Networks, considered as one of the key enablers of the future 5G networks [3]. For this reason and others, it is important that both uplink power control and HOs manage the system as efficiently and effectively as possible.

Both the downlink/uplink power control and HO decision algorithms need to consider the effect of interferences and therefore should consider the SIR [5]. We should mention that most of existing networks are very congested, thus could be fairly considered as interference limited system in contrast to satellite networks where thermal noise is dominating. For this reason SIR is usually considered instead of Signal to Interference plus Noise Ratio (SINR). In order to improve the speed of these algorithms it is beneficial to have a method of predicting the SIR at some location before receiving from the receiver status report about the channel. Furthermore, it would also be useful for cellular operators to be able to determine coverage maps of specific areas without the need of massive measurements campaigns.

In this paper, we suggest to use an Artificial Neural Network (ANN, [6, 7]) to predict SIR fields. In particular, we suggest a Radial Basis Network (RBN) [8], which is a type of Artificial Neural Network, that uses a Gaussian kernel as an activator, in contrast to a sigmoid function. Activation of such a neuron is accomplished by determining the distance of a feature vector from a predetermined centroid. We propose an RBN as the ANN because it is extremely good for problems such as function

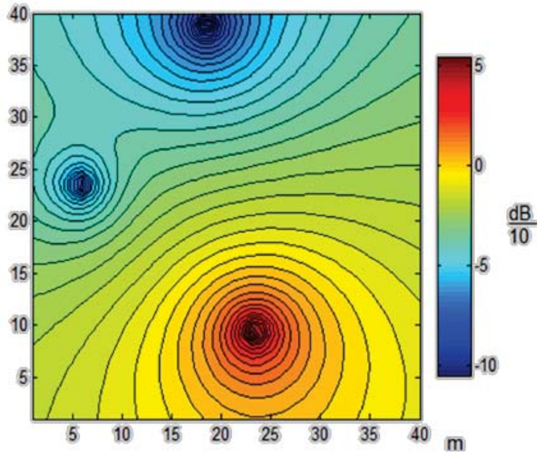

Fig. 1: A SIR coverage map of the target of the bottom transmitter.

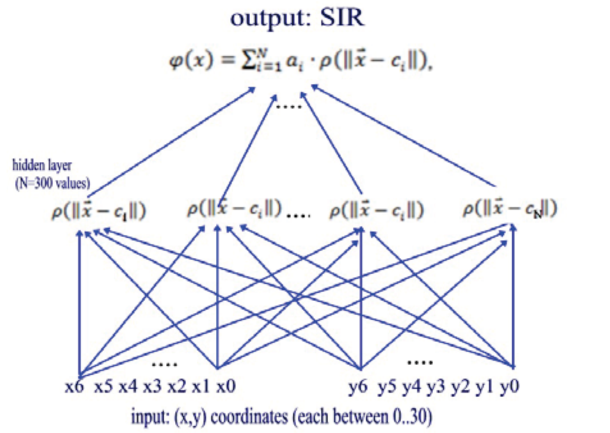

Fig. 2. The radial basis network used for the task of SIR learning, with N

approximation as well as pattern recognition, and thus, it can predict coverage maps extremely well if configured properly. ANNs are also exceptionally good at solving nonlinear classification problems as well as linear regression problems [9].

Predicting SIR using ANN has a great advantage over the current algorithms, since live ANNs are not only fast but also dynamic, and adapt to changes very well. For instance, if a new UE is introduced into the system or is removed from the system, the ANN will dynamically adapt itself. In addition, if a new physical obstruction is located in the region, such as a new building, there is no need for human intervention with the algorithm to calibrate it correctly; the ANN will adapt accordingly.

II. RADIAL BASIS NETWORK (RBN)

An RBN, in the realm of mathematical modeling, is a type of ANN. This particular type of ANN is very good in function approximations, time series prediction, classification and system control [9]. In general, an RBN typically has an architecture of two fully connected layers (in addition to the input layer) a layer with non-linear radial basis activation functions and a linear output layer. The input to an RBN is the feature vector $\vec{x} \in R^n$. The output y of an RBN is the linear combination of the activation of the neurons in the first layer (hidden layer) and the neuron parameters. The output can be viewed as the function $\varphi: R^n \rightarrow R$ given by

$$\varphi(x) = \sum_{i=1}^{N} a_i \cdot \rho(\|\vec{x} - c_i\|) \qquad (1)$$

where N is the number of neurons in the hidden layer, and a_i is the linear weight (normally stored in a matrix in the form of "W") and c_i is the centroid (center vector) for neuron i. The radial basis function ρ is given by

$$\rho(\|\vec{x} - c_i\|) = e^{-\beta\|\vec{x} - c_i\|^2} \qquad (2)$$

where β is the Gaussian dispersion parameter. The weights a_i and the centroids Ci, are trained by the learning mechanism, while the β parameter is determined in the design step. The Radial Basis Network was found to be an appropriate tool to learn and predict the coverage map, as explained below. In particular, we used the Radial Basis Network implemented by the newrb class applied by Matlab and documented in [10].

A typical SIR map (coverage map) is presented Fig. 1. In this scenario, the target transmitter is located on a grid at (23, 10) with two interferers located at (18.5, 39) and (5.8, 23.5). The interferers transmit at 100 and 10 Watts, respectively. The target transmitter transmit at 100 Watts unless explicitly mentioned otherwise. The task of the neural network is to learn the SIR in the network by sampling several points, without prior knowledge about the transmitters' location and power. A visual reference to the RBN architecture is presented in Fig. 2. The different points of the SIR maps are given as inputs to the network, and the SIR's exits in each point are the output of the network. The network parameters are determined after training the network given the measured data while the trained network is supposed to accurately predict the noise in other given points.

A. Training the RBN

There are different training schemes used for training the RBN, as described in [8]. The scheme used in our study is as follows. The first step to training an RBN is to determine the centroids to the neurons in the hidden layer. They are usually selected by using one of two methods. Either random vectors are selected as the centroids, or they can be found by using an unsupervised learning algorithm such as a clustering algorithm. In such cases, the centers of clusters can be found by running the algorithm on the samples of the training set [11]. Throughout this paper, the neurons' centroids are defined as the values of the input vector, as described in [10].

The aim of the second step is to determine the weights a_i of the output layer. The training process of a_i weights is very similar to that of a typical sigmoid ANN, and we use the back-propagation technique which finds the weights that minimize the error in the least squares objective function over the training set X. (Further documentation on how the RBN works and how it is trained can be found in [12, 13].) In particular, we train the network by the mathematical logarithm of SIR values, as described briefly in the next section.

B. Predicting Coverage Maps with RBN

Throughout this paper we will be looking at a scenario where we want to predict the coverage map of one transmitter when other transmitters cause interference on the same channel in a non-uniform manner, as demonstrated in Fig. 1.

Ensuing telecommunication engineering literature [14,15], the SIR in location k denoted SIRi(k) considers transmitter i and interfering transmitters j≠i. The average SIRi(k) can be defined as follows:

$$SIR_i(k) = \frac{\frac{p_i}{d_{ki}^{-\propto}}}{\sum_{j=1}^{N}\frac{p_j}{d_{kj}^{-\propto}} - \frac{p_i}{d_{ki}^{-\propto}}} \quad (3)$$

where p_i is the transmission power used by one of the transmitters i, d_{kj} is the Euclidian distance between transmitter j's coordinate and coordinate k, and ∝ is the path loss exponent parameter (set to 2 in our scenario). In this formula, i indicates the target transmitter. As we mentioned in section I we assume reasonably that our system is an interference-limited system therefore, along this paper we neglect the thermal noise. However, our model can be easily extended to consider the additional thermal noise generated which we neglect for purpose of simplicity.

As SIR values are given in logarithm form, natural slopes and curves emerge, making it easier for the RBN to learn the log form of the function, which is then converted back to the original SIR form.

Once the sample items are collected, they are used to train the RBN. In general, in order to start training the RBN, the Gaussian dispersion parameter (given in Formula (5)), should be determined. The best value for this parameter will vary with the scenario being modelled. Recall that the function learned by the RBN is of the form:

$$\varphi(x) = \sum_{i=1}^{N} a_i \cdot \rho(\|\vec{x} - c_i\|) \quad (4)$$

where

$$\rho(\|\vec{x} - c_i\|) = e^{-\beta\|\vec{x}-c_i\|^2}, \quad (5)$$

The following is the method we used for preparing an RBN as a means of predicting a coverage map. The first step is to collect the RBN's training set X, where each collected item contains the coordinate (x,y) of the item in the terrain map and the mathematical log of SIR value in that point, since this cause a more accurate capturing of the function values.

Thus, having a large β will give a smoother function approximation but it will forego fast changing values. Conversely, a β that is too small will require many neurons to fit the smooth parts of the function and therefore not generalize well. In Fig. 3 the tradeoff of using different β sizes on a coverage map can be seen. The figure describes predictions generated from an RBN with 300 neurons, after being trained with different Gaussian dispersion parameters (from top left to bottom right: 1, 3, 5, 10, 15). The figure in the bottom right is the original coverage map (target). It is clear that in this example β=3 provides the best approximation with the least anomalies.

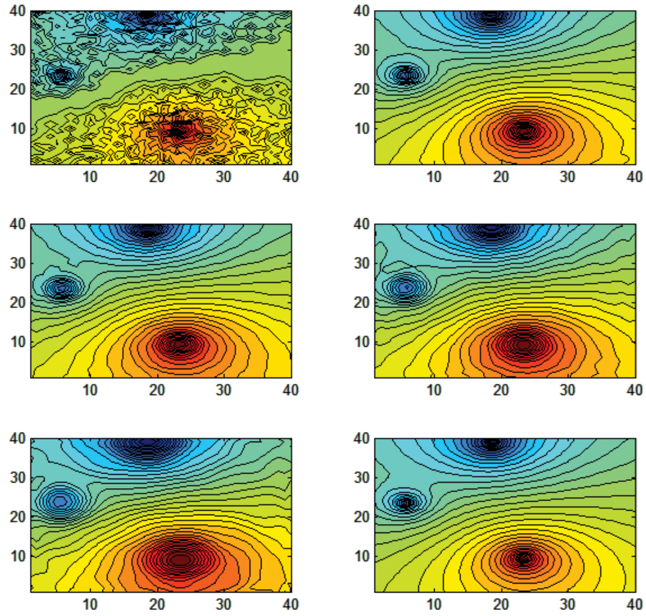

Fig. 3. Predictions generated from an RBN with 300 neurons.

Note that setting β=1 overfits the sample data, while setting β=5 or more exceedingly generalizes.

In general, we found that setting β = 2.5 provides the best approximations for coverage maps similar to our scenario. This was concluded after analyzing several simulations.

When a neural network is trained too well on a sample set, such that its predictions on values outside that sample set are extremely poor, the network is said to "overfit" the data. In our case, this occurs when β is too small compared to the number of neurons in the network. Therefore, the second most important factor in building an RBN is deciding the number of neurons to use. Although more neurons generally means better prediction accuracy, an exponential computational cost is incurred [8]. In our simulation, 300 neurons were the minimum amount necessary to provide acceptable accuracies in scenarios similar to ours. This was determined by checking the mean squared error.

It is important to note that the samples on which the RBN is trained should be taken randomly and uniformly in order to best capture the coverage map. In some cases, the SIR reports from the user equipment occur probabilistically closer to the transmitters themselves. In such cases, it is still possible to construct a functional coverage map, when samples are taken locally from points around the transmitters. It is apparent that if the samples are highly centralized, good prediction accuracy can be found in those areas.

III. SIMULATION RESULTS

We proceed by checking the accuracy of the RBN when using randomly created environments with different numbers and different locations of transmitters. We assume a 40*40 sized grid, where one 100 Watt target transmitter is located on a grid at a random place, and other interferer transmitters, with power of 10 or 100 Watts are located in random places on the grid. (A

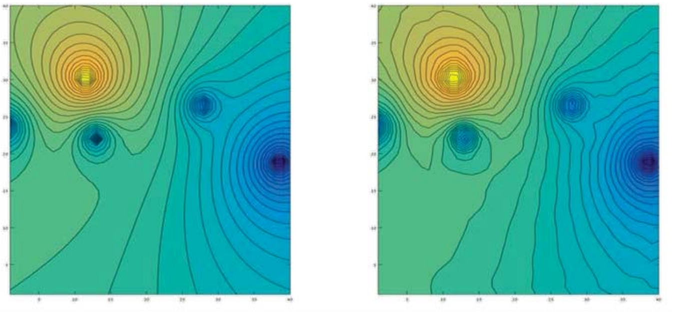

Fig. 4. left: A typical randomly created coverage map for 5 transmitters (4 interferers). Right: the coverage map learned by the RBN.

typical randomly created environment is shown in Fig. 4). For each randomly created environment, we sampled 100 Points, 90% of them were used for training the RBN, and the other 10% were used as the test set. For each number of transmitters between 2..10 (i.e., 1..9 interferers), we ran 100 randomly created environments, and collected the NRMSE (normalized rooted mean squared error), computed on the test set. The formula of the NRMSE is as follows:

$$NRMSE = \frac{RMSE}{max(y_{real}) - min(y_{real})}$$

where

$$RMSE = \frac{1}{n}\sqrt{\sum_{t=1}^{n}(y_{real} \quad - y_{predicted})^2}$$

Table I presents the RMSE for different numbers of transmitters.

TABLE I. *RELATIVE ERRORS FOR PREDICTED SIR*

# Transmitters	RMSE
2	0.000122
3	0.000717
4	0.000175
5	0.000325
6	0.000697
7	0.000341
8	0.000084
9	0.000484
10	0.000077

As shown, the RMSE remains low as the number of transmitter increases. In other words, the RBN gives a good prediction for the SIR values for different number of transmitters.

IV. CONCLUSION

In this paper, we have shown how to use radial basis networks for predicting coverage maps for radio networks. In order to do so we proposed taking the logarithm of the SIR values so that the RBN could learn the interference effects much better. However, while training the RBN, we noticed that the way the RBN is configured can cause overfitting if too may neurons exist, which are trained to return the exact output value of the train set. Noting this, we recommend good empirical parameters based on MATLAB simulations, which could predict the SIR in the control set with a high accuracy. Given the appropriate parameters, the Radial Basis Network successfully predicted the coverage maps with low error for different number of interferers. Thus, we suggest the RBN as a useful method for coverage map prediction. A direction for future work is to find quick and efficient processes to adapt the trained RBN to scenarios of small changes in the environment.

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