A Novel Site Adaptive Propagation Model

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***Abstract*—A site adaptive knowledge guided neural network (KGNN) propagation model, using Hata model as knowledge base (KB) is presented. It adapts to measured data with rapid convergence.**

***Index Terms*—Artificial neural network (ANN), knowledge base (KB), propagation loss.**

I. Introduction

SPECTRUM of models for radio propagation loss prediction contains closed form empirical formulae on one end and more accurate computer intensive deterministic methods, requiring detailed terrain database, on the other end. The usefulness of this spectrum to the broader propagation community is revealed in a recent survey [1]. The preferred one is normally the empirical formulae, which can be represented in standard form [2] as written in (1)

$$L_p = f(h_b, f_c, h_m, d, \Delta h). \tag{1}$$

Here, L_P, h_b, f_c, h_m, d, and Δh are respectively the path loss, the base station antenna height, the frequency, the mobile antenna height, the distance between Tx and Rx antennae, and the degree of terrain undulation known as intercede range.

The closed form empirical models suffer from two major disadvantages [3]: 1) impracticality of using large available data in modeling, and 2) lack of adapting flexibility to various terrain databases and terrain. The desired characteristics of radio propagation empirical loss prediction models include [3]: 1) nonexact analytical formulation, 2) limited accuracy, 3) available quantity of data for modeling is medium, and 4) adaptive flexibility to various terrain database and terrain. These characteristics closely match those of artificial neural network (ANN), which is an adaptive and open empirical model. The complexity of ANN-based models lies somewhere in the middle of the spectrum of the radio propagation models. Hence, it has been investigated as a feasible model [3]–[6] to predict empirical results. However, they are prone to problems like slow convergence and local minima traps during training resulting in unpredictable results. Overcoming local minima problem needs to increase the number of neurons in the hidden layer and, hence, higher computational complexity.

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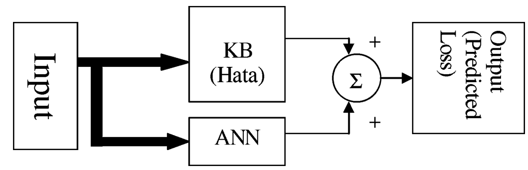

Fig. 1. Schematic of the proposed KGNN.

II. Knowledge Guided Neural Network (KGNN) Model

This letter implants Hata model [8] as knowledge base (KB) to guide the ANN modifying KBNN concept [10] in an attempt to minimize the above problems. In this modification, the KB is taken as a hidden neuron (Fig. 1), whose connecting weights are fixed as unity. Initially, all other weights are initialized to zero. Thus, initially, the KGNN output is the Hata models output, which is an approximation to the desired result. Hence, the error is near the global minimum. Now by updating the weights, we reach the global minimum easily, avoiding the local minima. Weight update employs standard back propagation along with the learning rate and momentum [9].

III. Simulation Results

The proposed model is trained with Okumura's [7] measurement in Tokyo area assuming a quasismooth terrain ($\Delta \mathrm{h} \approx 20\ \mathrm{m}$), which led to the Hata model that is being used as the KB in this work. It is well known that the ANN has Universal generalization capability. This means, it can be trained, validated, and tested with various data sets of same dimensionality (i.e., the dimensions of the respective inputs and outputs remains same). To be specific for the present problem, if an ANN model can be developed for a specific terrain, then the same structure can adopt a new set of weights for another terrain, exploiting its generalized adaptation behavior. Thus, such models automatically become site adaptive in nature.

A $4 : 5(4 + \mathrm{KB}) : 1$ KGNN was trained with 200 training patterns. The four input neurons are h_b, f_c, h_m, and d. Out of the five hidden neurons, one is KB and others use $tanh(\cdot)$ activation function. The activation function for the output neuron is *linear*. Its results are compared with a conventional ANN that has the same structure with all the five hidden neurons having $tanh(\cdot)$ activation function. The mean square error (MSE) for the Hata, ANN, and KGNN with respect to measured data are found to be 6.38, 4.42, and 1.51 dB, respectively.

Fig. 2 compares the performance of various models with measured data. It is observed that the result of the ANN model acts like a linear curve fitter to the measured data. This may be due to a lower number of hidden neurons and pure linear transfer function in the output neuron. It illustrates the fact that in conventional ANN, the hidden layer neurons play an important role in adapting the nonlinearity of the network output. The more the

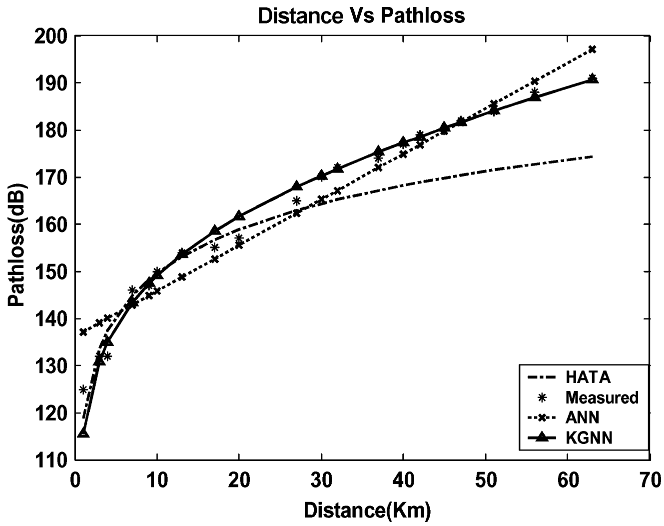

Fig. 2. Comparison between measured, Hata model, ANN, and KGNN (path profile at $f_c = 1318$ MHz, $h_b = 140$ m, $h_m = 3$ m.).

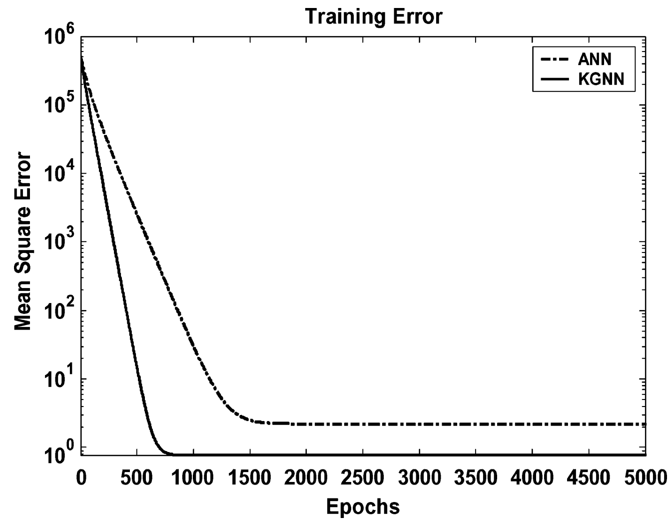

Fig. 3. Mean square training error of KGNN and ANN, with back propagation training.

nonlinearity, the more should be the number of hidden neurons. Contrary to this, the KGNN follows the measured data more accurately, with the same number of hidden neurons. It is a significant advantage of adding the KB, which ensures that the output pattern is followed. Thus, the KGNN model yields more accurate results with addition of a low complexity adaptive neural structure compared to that of the conventional ANN counterpart. On the other hand, the simple Hata model also follows the experimental pattern up to about 20 kms beyond which the deviation increases with distance. In the KGNN model, the ANN part synchronously alleviates the deviation and, hence, better matching in the former is maintained throughout.

Fig. 3 depicts the MSE of the KGNN and ANN models. The convergence or learning of the KGNN is observed to be faster and better. What is important here is the interpretation of this result vis-à-vis that of Fig. 2. As discussed earlier, the ANN fails to match with the nonlinearity associated with the experimental results which is not the case for KGNN. This undoubtedly reveals that the ANN has converged to a *local minima*, where as the KGNN has converged to the *global minimum*.

IV. Conclusion

This letter has proposed a novel hybrid model consisting of a KB in parallel with a low complexity ANN structure. Through exhaustive computer simulation it has been demonstrated that the proposed hybrid model outperforms the corresponding high complexity ANN model reported in the literature. In addition, the proposed model offers least MSE and convergence time compared to its ANN counterpart.

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