5. Neural Networks in Mobile Power Control

As the radio channel statistics are constantly changing, and its parameters may be difficult to measure, neural networks may offer solutions to the received power level estimation problem, as well to a variety of other mobile communications system problems. Neural networks (NN) are attractive mostly because of their widely used abilities to learn the signal statistics, or other possible dependencies within the input data, if the network is properly constructed. This learning can be designed to be done either off-line with known input data, or on-line, i.e., the neural network can be made adaptive. A real-time adaptive neural network is naturally a computationally heavy solution but its advantages are also obvious.

Neural networks [Fre91], [Gao95] are capable of learning relations between input data and desired output data. In the context of this Thesis, neural networks could be used either in the actual prediction, or to estimate signal properties. In the former case, the input data to the network is a received power level history, and the output is the predicted power level. In the latter case, the same input is associated, for example, with the mobile speed, or with the length of the near-optimum polynomial predictor. In any case, the network has to be trained with either a known training set of input and output data covering the whole range of possible channel conditions, or with a suitable channel model. Also, as the polynomial prediction has been shown to be effective for power prediction, a representative set of polynomials could also be employed in the training. In operation, online adaptation can also be used regardless of whether the NN was also trained off-line or not.

5.1 Introduction to Neural Networks

One example of a possible NN topology [Fre91] is shown in Fig. 5.1. No processing is done in the input layer but the inputs are only distributed to the inputs of the computing elements in the next layer, which may be either a hidden layer, or the output layer. A possible hidden layer, or output layer, computing element, i.e., a neuron, is illustrated in Fig. 5.2. The neuron computes a weighted sum s of all its inputs x_i, and applies an activation function f to the sum. Result is then either a network output, or a hidden layer neuron output which is distributed to all the neurons in the next layer. Letting O denote an output of a neuron, it is given by

$$O = f\left(\sum_{i=1}^{M} w_i x_i\right). \tag{5.1}$$

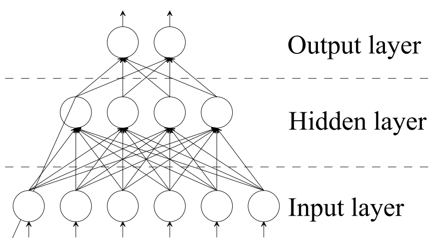

Fig. 5.1. A neural network with K=6 inputs and L=2 outputs.

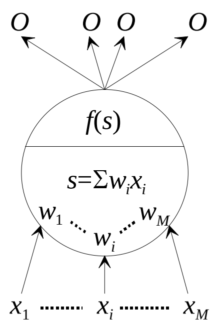

Fig. 5.2. A hidden layer or an output layer computing element with inputs x_i, weights w_i, an activation function f, and output O. In the first hidden layer M=K.

The activation function f may be, for example, a linear function, or a sigmoid function [Fre91]. Activation function is used to control the behavior of the outputs and intermediate results of the network to improve learning and to achieve desired outputs. The network in Fig. 5.1 is taught [Fre91], for example, by presenting a training input vector to the network inputs and calculating the outputs. The outputs are compared to the known desired outputs, and the errors are propagated down the network in the fractions according to the weights in each computing element. The weights are then updated with the backward propagated errors so that if the same input is presented to the network again, the output is closer to the desired output as before the training took place. This training approach is called error backpropagation [Fre91]. Training may also be continued online if desired. The network topology can either be selected by trial-and-error method, or an algorithmic optimization method may be used [Gao96], [Gao97a], [Gao97c]. As the intention of this text is to give the reader an idea of the possibilities of the NNs, let us not go now any deeper into NN training methods, or to topology optimization.

Generally, the NN topology has been found by trial and error methods, or by reducing the size of the NN until performance degradation is seen. The Gao brothers have successfully applied a criteria of predictive minimum description length (PMDL) [Ris84] to NN structure optimization [Gao96], [Gao97b], [Gao97c]. Their NN work concerning mobile power control is short described in the next section.

As nonlinear systems, NNs do not posses frequency responses in traditional sense. Even so, it is very insightful for a NN designer to estimate the properties of the networks trained, or under training. This also aids the designer in applicability considerations. In [Var97], input dependent frequency response estimates are obtained for a NN originally designed for Rayleigh fading prediction. Responses are estimated for sinusoidal [Nee90] and WGN input signals, and also time domain behaviors for step and triangular signals are observed. Similarities of the frequency response estimates from different input reflect good generalization capabilities of the NN.

5.2 Examples of Neural Networks in Mobile Power Control

In [Gao96], [Gao97c] a hybrid neural network based predictor, Fig. 5.3, is constructed for Rayleigh fading prediction. With online adaptation, the NN structure in Fig. 5.3, exhibits 3 to 5 dB better SNR gains than those obtained using H-N predictors but naturally the adaptive NN structure is computationally severely more expensive than the H-N predictor solutions. In [Gao96], [Gao97c] structures of both NNs, functional link NN, and multilayer perceptron, Fig. 5.3, are optimized using the PMDL principle. The functional link NN is essentially an adaptive FIR fed from a tapped delay line. Output of the functional link NN, Fig. 5.3, in turn feeds the tapped delay line input of the multilayer perceptron.

In [Gao97a] a Modified Elman Neural Network (MENN) based DS/CDMA closed loop power control system is presented. The MENN is shown in Fig. 5.4. This network type has the advantage of having a context layer. In the context layer, no actual processing is done but the nodes act as inner memory units storing the “context” in which the network is currently operating. Due to the internal context nodes and adaptive connection weights w, the structure is advantageous in identifying dynamic systems without knowledge on their exact order [Gao97a]. Also, a multiple model control system is sketched that consists of several system model identified off-line [Gao97a]. Switching between the models can be done, for example,

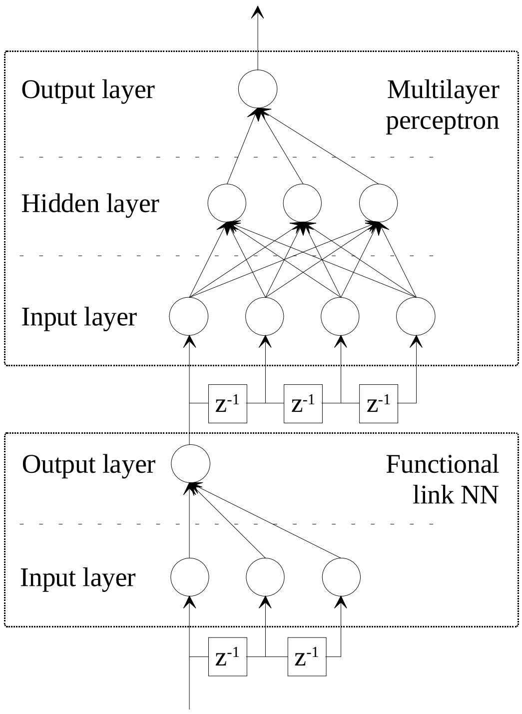

Fig. 5.3. A hybrid NN-based predictor structure (of an arbitrary size, for example only). Adopted from [Gao97c].

based on the mobile speed estimates. The system also includes a gain control subsystem which is necessary for obtaining quick power control responses when abrupt environmental changes occur, say when a mobile suddenly appears from behind a building creating a greatly improved radio propagation channel with a new LOS path between the mobile and the base station. In [Gao97a], MENN was able to reduce the deep fading to allow for successful communications also during some fades. The power control system presented in [Gao97a] is actually parametrized for deep fade reduction, and as such is thus not exactly suited for obtaining constant, and minimum acceptable, received power levels at the base station but the structure itself has great potential for the power control applications.

Two other interesting concepts are using optimal neuro-fuzzy predictors [Gao97b], and a temporal difference method-based prediction [Sut88], [Gao98] in mobile power control systems. In [Gao97b], structure of the neuro-fuzzy predictor is also optimized using the PMDL principle [Ris84]. The temporal difference-method based predictor [Gao98] is also based on MENN network structure, Fig. 5.4, while in contrast with the common direct signal value prediction, the actual function is designed for predicting the probability of deep fade incidents several steps ahead [Gao98]. The basis of the temporal difference method is to consider the difference between two successive predictor outputs as the prediction error [Sut88], [Gao98].

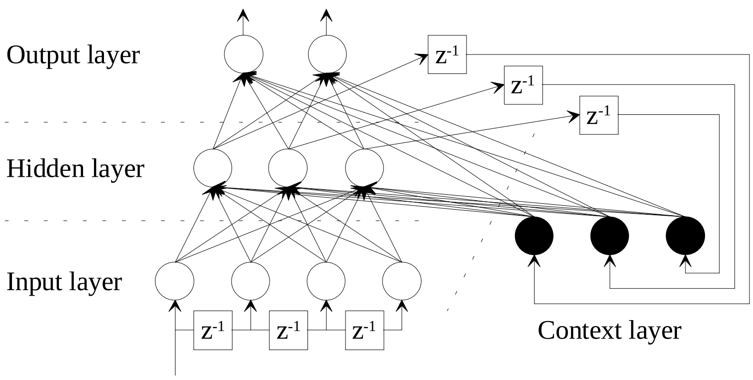

Fig. 5.4. Basic structure of a MENN of the size, selected for example only, K=4 inputs from a tapped delay line, L=2 outputs, three hidden layer and C=3 context layer neurons. Adopted from [Gao97a].

Possibilities of applying NNs to power signal prediction are numerous. NNs can be used to do the actual prediction, either direct power prediction, or prediction in components. They can be applied to radio channel modeling [Ibn97], or to adaptive channel equalization [Kec94]. In [Miy93] NN systems has been suggested for CDMA MUD. Furthermore, they could be used as signal derivative detectors, or to directly output the momentary predictor parameters. These application possibilities make NNs an interesting research topic in the field of power control systems. One could even think of a pure neural network power controller that would directly generate the power control command to be sent to the mobile unit [Gao97a].