Chapter V

Conclusion

This thesis presents a generalized mathematical model to improve the fault immunization of the feedforward neural networks. This mathematical model can be used by the input data in the interval [0,1]. We show that the maximum fault immunization of the neuron can be achieved by relocating the weight vector to form the decision hyperplane in the middle of the empty channel between two input classes. The immunization problem was transformed to be the problem of optimizing a cost function, which is easier to solve. There are two steps for solving this problem. First, the neural network is trained until it converges. Then, a new weight vector can be achieved by using the modified random optimization algorithm. In this thesis, the Pareto's optimality concept was used to combine the target error function with the sum of all location errors in the neural network. The immunization is globally performed throughout the whole network and is integrated as a part of the training process. We can determine the proper weights for both analog and digital networks. From the experimental result, our technique can improve the fault immunization capability of the feedforward neural network. The limitations of our technique are (a) the generality of the algorithm that depends on the generality of the boundary vector finding algorithm, and (b) our assumption that the training set is expected to be the fully representative of inputs of the network during application, which is an ideal condition. The first limitation can be solved by the method of [25]. The second limitation is still a tough problem in case the input data are incomplete. Therefore, we need some theories for boundary vector prediction. If we can predict the location of the boundary vectors, the neural network will exhibit excellent ability to generalize their response and fault tolerance in case when the unseen data are not in the training set.