Multi-layered neural networks of the back-propagation type are well known for their universal approximation capability. Already the standard back-propagation training algorithm used for their adjustment provides often applicable results. However, e cient solutions to complex tasks currently dealt with require a quick convergence and a transparent network structure. This supports both an improved generalization capability of the formed networks and an easier interpretation of their function later on. Various techniques used to optimize the structure of the networks like learning with hints; pruning and sensitivity analysis are expected to impact a better generalization, too. One of the fast learning algorithms is the conjugate gradient method. In this thesis, we discuss, test and analyze the above-mentioned methods. Then, we derive a new technique combining together the advantages of them. The proposed algorithm is based on the rapid scaled conjugate gradient technique. This classical method is enhanced with the enforcement of a transparent internal knowledge representation and with pruning of redundant hidden and input neurons inspired by sensitivity analysis. The performance of the developed technique has been tested on arti cial data and on real-world data obtained from the World Bank. Experiments done yield promising results. Our method is comparable with the original methods when considering their superior feature, i.e. convergence rates, generalization capabilities and number of used hidden and input neurons.