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GROWING RADIAL BASIS FUNCTION NETWORKS USING GENETIC ALGORITHM AND ORTHOGONALIZATION

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Abstract. *With the recent popularity of the neural networks for modeling nonlinear systems, there is a growing need for a systematic and autonomous way to simultaneously determine the optimal network size and parameters. This paper tries to meet such demand by presenting a new growing algorithm for the radial basis function networks (RBFN). In the proposed algorithm, a new hidden node is added to the RBFN in sequence while previously found hidden nodes remain intact. Genetic algorithm searches for each new hidden node after calculating the fitness of candidate hidden nodes via a computationally efficient orthogonalization procedure. The proposed algorithm is compared with conventional GA-based methods and non GA-based growing algorithms in the literature through benchmark examples to demonstrate its superior performance in model-building without any priori knowledge. Lastly, the proposed algorithm is successfully applied to a task of modeling the disk grinding process based on the actual process data collected from electronics industry.*

Keywords: Genetic algorithm, Radial basis function networks, Modeling, Function approximation

1. **Introduction.** Neural networks have found many applications in system identifications, controls, function approximation, and signal processing due to their ability to approximate arbitrary nonlinear functions [1,2]. Since many neural networks are highly nonlinear in parameters and structures, they usually require extensive computation for training and suffer from convergence to a local minimum depending on the initial choice of parameters and updating rate. Radial basis function networks (RBFN's), on the other hand, have gained their popularity because a simple linear least squares technique can be adopted for their training once their nonlinear parameters in hidden layers are properly identified. A critical question is how and how many hidden nodes should be chosen to yield the best performance of RBFN.

Classic methods for determining the number of the hidden radial basis function (RBF) nodes can be classified into 3 categories in large. In the first category, the hidden nodes are added to the network one at a time while previously found RBF nodes remain intact. Examples in this category include the forward selection methods such as the orthogonal least-squares (OLS) algorithm by Chen *et al.* [3] and its gradient-based adaptive version or the adaptive OLS (AOLS) algorithm by Chng *et. al.* [4]. Both methods suffer from the high dependency of their learning performance on the preset values of the hidden node