

**DYNAMICAL NEAR OPTIMAL TRAINING FOR  
INTERVAL TYPE-2 FUZZY NEURAL NETWORK  
(T2FNN) WITH GENETIC ALGORITHM**

**A Thesis Submitted in Fulfilment of the Requirements of the Degree of  
Master of Philosophy**

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 **ABSTRACT**

Type-2 fuzzy logic system (FLS) cascaded with neural network, called type-2 fuzzy neural network (T2FNN), is presented in this paper to handle uncertainty with dynamical optimal learning. A T2FNN consists of type-2 fuzzy linguistic process as the antecedent part and the two-layer interval neural network as the consequent part. A general T2FNN is computational intensive due to the complexity of type 2 to type 1 reduction. Therefore the interval T2FNN is adopted in this paper to simplify the computational process. The dynamical optimal training algorithm for the two-layer consequent part of interval T2FNN is first developed. The stable and optimal left and right learning rates for the interval neural network, in the sense of maximum error reduction, can be derived for each iteration in the training process (back propagation). It can also be shown both learning rates can not be both negative. Further, due to variation of the initial MF parameters, i.e. the spread level of uncertain means or deviations of interval Gaussian MFs, the performance of back propagation training process may be affected. To achieve better total performance, a genetic algorithm (GA) is designed to search better-fit spread rate for uncertain means and near optimal learnings for the antecedent part. Several examples are fully illustrated. Excellent results are obtained for the truck backing-up control and the identification of nonlinear system, which yield more improved performance than those using type-1 FNN.

Index terms – Interval type-2 FNN, Dynamic optimal learning rate, Back propagation, Genetic algorithm.

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This thesis has not previously been submitted for a degree or diploma in any university. To the best of knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

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