Reallocation of Mesh Points in Fluid Problems
Using   Back-Propagation Algorithm

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Abstract--- This paper deals with the construction, training and application of neural networks to compute adaptive mesh points through reallocation scheme on different types of double steps channels. We use back-propagation neural networks on three layers (one input, one hidden and one output) with Adaptive Smoothing Errors (ASE) technique   to reallocate mesh point and crowd them into the most important region in the channels according to the fluid flow behavior. Results of numerical experiments using finite element method are discussed and included to validate the process and to demonstrate the performance of the neural networks on any type of channels shapes.

Index Terms – Neural Networks, Back-Propagation Algorithm, Adaptive Mesh, Finite Element Method.

1. INTRODUCTION

Mesh generation technique on any channel geometry will lead to elements of varying shape and size. It also describes how to grade or adaptively refine and coarsen the mesh in FEM (Finite Element method) [1],[2] and [3]. The general objective of the Adaptive Method (AM) is to change the model, mesh form, and mesh size to improve the quality of the numerical solution of the fluid problems through channels. In this paper we use AM on the double steps channels geometry to study flow behaviors. Numerical solution on this type of channel is unstable, so that it is important to introduce AM to produce efficient distribution on the channel's mesh points. The main role of AM is to reduce the effect of the errors for all mesh points at the domain which satisfy the following criteria:-

$$Min(Max \ Error \ ) \ for \ all \ elements$$

$$until \quad Error(element) = Consant \quad \forall \, elements$$

We suggest a new learning model for AM by using BPANN (Back-Propagation Algorithm Neural Networks) to compute AM for regular and irregular shapes in fluid problem. The architecture of BPANN incorporation both the forward and backward phases of the computation, these phases work as a learning system and it based on "*error correction learning rule*". Forward phase interest to account on the layer index by L extends from the input layer L=0 to the output layer L=2, while the backward phase referred to as a sensitivity network for computing the local gradients for all neurons.

Rosenblat (1958) [10] is the pioneer in MLPPNN (Multi-Layer Percpetron Neural Networks). Windrow et al (1990) [11] discuss the BPA modifications, Moria, M. 1994,1996 [7],[8] applid smoothing and reallocation mechanism on the pattern sequence and pattern memory respectively by using nonmonotonic neural network. Mui, A. et al (1994) [6] applied adaptive neural networks for pattern recognition. K. R. AL-Rawi,[5] 1999, used artificial neural networks to build new neural network architecture for classified multi-valued input patterns.

2.   NEURAL NET ARCHITECTURE

Neural nets or multi-layered perceptrons are connected layers of neurons and may be "trained" to learn specific concepts from examples. Basically, there are four key parameters that characterize a neural net architecture: (1) the number of layers, (2) the number of neurons in each layer, (3) the kind of connectivity among layers and (4) the kind of activation function used within each neuron.

A neural net can in principle have any number of layers with each layer having a number of neurons. The most common neural net architecture is comprised of 3 layers: The first layer is called the input layer, the second layer is called the hidden layer and the third layer is called the output layer.