Artificial Intelligence based Levenberg Marquardt approach to solving Tsunami Wave Propagation Model

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Abstract- This manuscript deals with the Earth's most impulsive and perilous natural disaster well known as Tsunami mathematical model. Tsunami propogate with an utmost speed and have incredible energy. The governing equations are of partial differential which are further handled by the Maching learning based Back Propagation method, known as Levenberg-Marquardt approach. Here we generate 1000 data points. The 70% of data are used for training, 15% for testing and 15% for validating. The plot of mean squre error (MSE) between the exact solution and ANN are discussed through graphs.

Keywords– Tsunami Model, ANN, Matlab Simulation.

1. INTRODUCTION

Tsunami waves that form in the open ocean travel at high speeds but are barely noticeable. Now the waves are approaching the shore where the water waves decrease. Unexpectedly, the waves that initially seemed harmless suddenly gains a gigantic amplitude form a devastating tsunami. The slowmoving oceans beds onetime interrelate like this. One tectonic plate sliding under another. This continues to subsequent bulging upper layer and waves become longer. Several authors have deliberated this model mathematically and solved by several techinques to demonstration the impact of tsunami waves on earths Environment [1-10].

2. ANN-LM METHOD

The artificial neural network based Levenberg-Marquardt algorithm is a controlling optimization technique to trained the neural network and minimizing the error providing input and output datas by least sqaure method. The ANN-LMA is hybrid technique combined from Gradient Descent and Gauss-Newton method. The Machine learning based Artificial neural network (ANN) is a type of computational prototypical inspired by the functioning of biological neural network in human brain. It is a type of deep learning that uses to acquire about the realtionships of input/output datas and understanding the complex patterns. The principal components of ANN are Neurons (Nodes), weights, Activation functions, Back Propogation, Loss calculations, Optimzation and Training of the input datas. Nowadays, ANN are widely used in Fractal-Fractional type differential equation, Nanofluid dynamics, Mathematical modelling etc., [11-17].

In this paper we have derived 1000 data points and trained the data by ANN-LMA. Out of which 70% is used for training, 15% is for testing and 15% is aimed at validating. We inspect the mean square error (MSE), Comaparative study between the Numerical methods and ANN-LM, Error plots and regression analysis. Through MATLAB nntool/nftool command we trained the obtained data and compared with the exact solution.

Theses are the step-by-step method for trained the data:
Step-1 Generate the input and target datas
Step-2 Use Matlab builtin function nftool/nntool to store input (independent variable(s)) and ouput (dependent variable(s)) data.
Step-3 Use Activation functions (Sigmoid, Tanh, linear etc.) to approximate the function datas.
Step-4 Create ANN-LM structure.
Step-5 Established Training Parameters.
Step-6 Train the network (Input/Output).
Step-7 Examine and Predict the output data.
Step-8 Evaluate the performance of ANN-LM.
Step-9 See the results obtained by ANN and Numerical method.
Step-10 Assess the Comapritive results, MSE, Validating performance, Error histogram and Regression analysis.

3. TSUNAMI MODEL

The tsunami pde are as follows:

$$\frac{\partial h(x,t)}{\partial t} = -\gamma \frac{\partial u(x,t)}{\partial x} + F(x,t) \quad (1)$$

$$\frac{\partial u(x,t)}{\partial t} = -g \frac{\partial h(x,t)}{\partial x} - \varepsilon\, u(x,t) \quad (2)$$

with the initial conditions

$$h(x,0) = h_0, u(x,0) = u_0.$$

for $\gamma = 0.4$, $g = 9.81$, and $\varepsilon = 0.1$

$u(x,t) = 1 + 0.5 \sin(\pi x). \exp(-t)$

and

$h(x,t) = \exp(-t)\cos(\pi x)$.

Here $h(x,t)$ denotes the tsunami wave height and $u(x,t)$ be the tsunami waves horizontal velocity, γ be the uninterrupted water waves, g be the gravitational velocity, ε be the friction parameter and F(x, t) be the source terms.

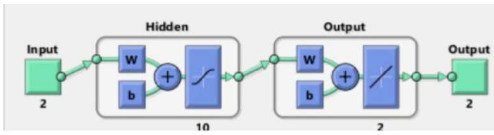

Figure 1: Schematic diagram of ANN

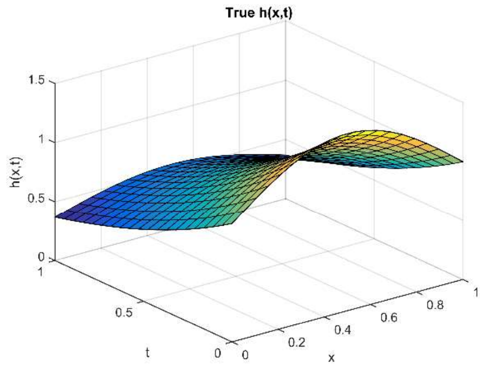

Figure 2: Solution of h(x,t) analytically

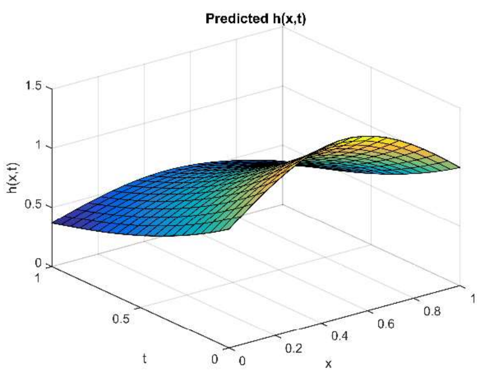

Figure 3: Solution of h(x,t) by ANN

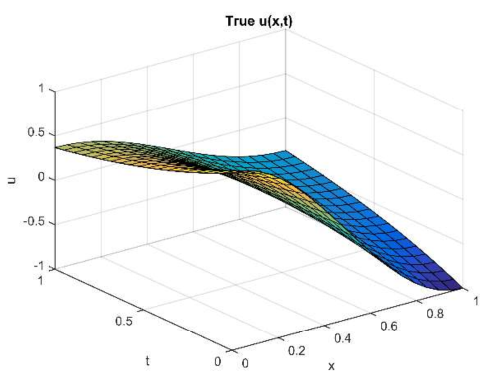

Figure 4: Solution of u(x,t) analytically

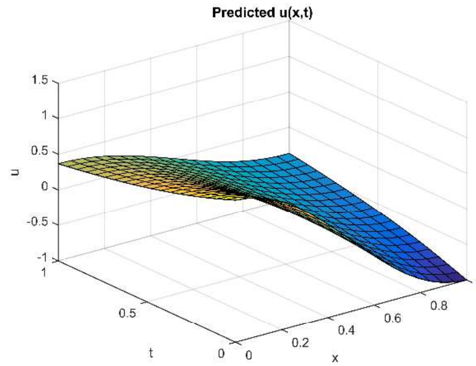

Figure 5: Solution of u(x,t) by ANN-LM

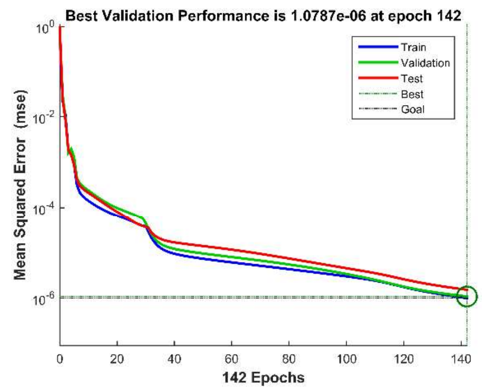

Figure 6: ANN-LM training for Validating

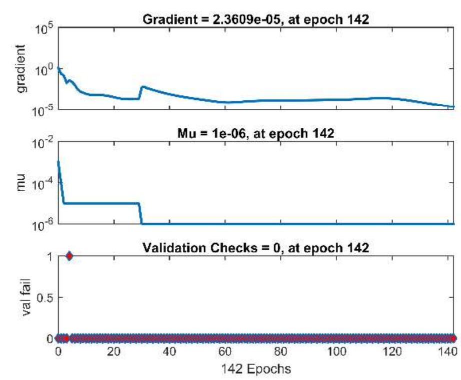

Figure 7: Estimation of Gradient and Mu at 142 epochs

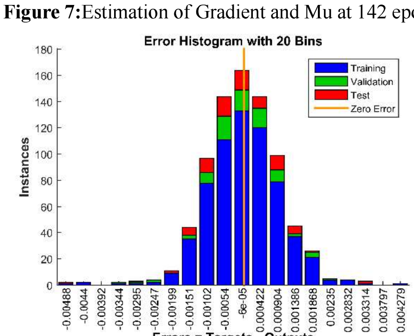

Figure 8: Error Histogram by ANN-LM

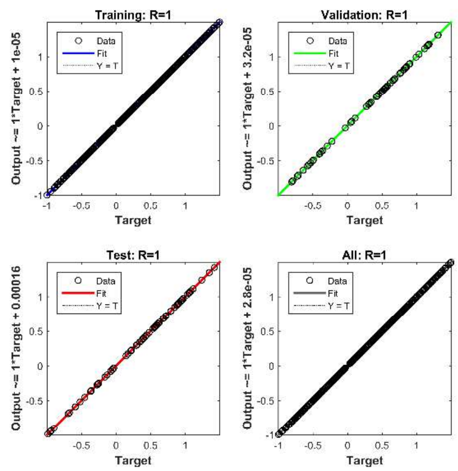

Figure 9: Regression analysis by ANN-LM

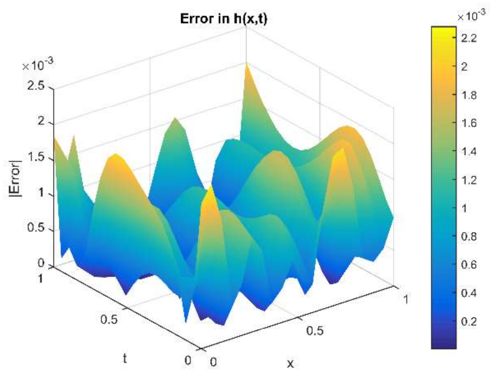

Figure 10: Absolute error by ANN-LM

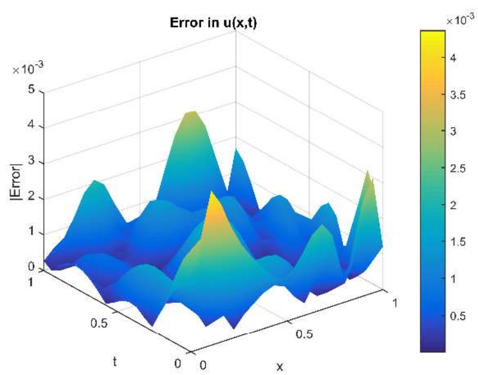

Figure 11: Absolute error by ANN-LM

4. CONCLUSIONS

In this paper we have discussed the machine learnimg approach to solve the tsunami model. Schematic diagram is presented in Figure1. Figures 2 and 3 respectively plotted for tsunami wave height. It is concluded that the both graphs are identical. Figures 4 and 5 are respectively plotted for horizontal velocity with time and spatial references. It shows an equivalence between the exact and ANN prediction with 1000 data points. Figure 6 portrays to examine the input and output datas at 142 epochs moreover ANN-LM trained the network data through best validating performance of 1.0787e-06. Figures 7 and 8 draws for testing the data with Gradient and Mu (2.3609e-05, 1e-06). The Regression analysis between the Input and targets data are plotted in figure 9 and $R \approx 1$ emphasise an excellent realtion with the predicted (ANN-LM and exact solutions. Figures 10 and 11 are respectively strategized for absolute errors of h(x, t) and u(x, t).

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