A New Artificial Neural Network Approach for Fluid Flow Simulations

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Abstract: In this research we describe our attempt to get instantaneous numerical simulation for fluid flow by using Artificial Neural networks (ANN). Such simulation should provide a reliable perception about the fluid behaviour with respect to both momentum and energy equations. In addition to the preceding recorded data, the proposed method consider the geometrical boundaries profile as a major contributions for ANN training phase. Our study is driven by the need of rapid response especially in medical cases, surgeon diagnosis, engineering emergency situations, and when novel circumstances occurs. Furthermore, the existing computational fluid dynamics tools require long time to response and the present of professional expert to set the parameters for the different cases. In fact, ANN can deal with the lack of proper physical models or the present of uncertainty about some conditions that usually affect the outcomes form the other approaches. We manage to get acceptable result for 1D-flow equations with respect to both energy and momentum equations. Our ANN approach is able to handle fluid flow prediction with known boundaries velocity. This approach can be the first step for neural network computational program that can tackle variance type of problems.

1 INTRODUCTION

The ANN seem to be the right tool to find quick results from recorded data due to its flexibility and automatic perception. In fact, ANN can deal with the lack of proper physical models or the present of uncertainty about some conditions which usually effect the outcomes form the other approaches. Commonly, CFD solutions still have to be validated against reliable results, such as experimental or benchmarks data, in order to gain confidence in the outcomes. Since we have to compare our results to previous data why not try from start to use this comparisons to predict the fluid characteristics and get instant feedback. ANN has been employed in heat and mass flow processes mostly in the present of uncertainty conditions. There are several research regarding the predictions of heat transfers, mass flow rate, aerodynamic coefficients and statistical quantities (Islamoglu et al., 2005, Liu et al., 2002, Díaz et al., 2001, Rajkumar and Bardina, Panigrahi et al., 2003).

Motivated by Benning, Becker, and Delgado (Benning et al., 2001, Benning et al., 2002) propagation neural networks model to predict the flow field for steady flow around a cylinder, we try here to predict distributions of thermal and flow variables in a domain. We reverse Hirschen and Schäfer methodology (Hirschen and Schäfer, 2006) to add the geometrical boundary as a major input for our ANN model. They use ANN in conjunction with evolutionary strategy to optimize the geometry for fluid flow.

In the proposed paper, we first list the types of the appropriate network architecture that can handle the fluid characteristics efficiently. Second, we choose the proper training method to insure accurate and effective response from the numerical ANN training database. Then, we combine geometrical boundaries profile and the ANN training data to generate the simulation. Finally, we discuss and illustrate our initial results.

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2 METHODOLOGY

The MATLAB -Version 7.0 (R2010b) - Neural Network Toolbox is used to simulate our ANN model. The ANN training data is obtained from the Analytic solution for the parabolic heat equations. We start by building the numerical database to be the ANN training data. The Crank–Nicolson method and the implicit method is implemented to find the numerical solution. The collections of known input-output arrays from numerical data are exposed to the neural network in order to teach it. Then the weight factors between nodes are adjusted until the specified input produces the wanted output. Through these tunings, the ANN learns the correct input-output flow predictions. Our ANN is applied to transient two dimension domain to predict the flow behaviour. Then we manipulate the network architecture to ensure it can handle the fluid characteristics efficiently. Finally, we test the ANN responses under different training methods to make sure the system is optimized.

The simple steady state heat transfer is validated in order to test the ANN ability to predict the flow characteristics. The geometrical boundaries is investigated and its effect on the results is measured. Our approach satisfy the energy and the momentum equations tested a transient heat flow. The MATLAB command tic-toc is used to calculate how long the ANN response. Then the responses was compared with other numerical results.

3 RESULTS

3.1 Steady State Heat Transfer

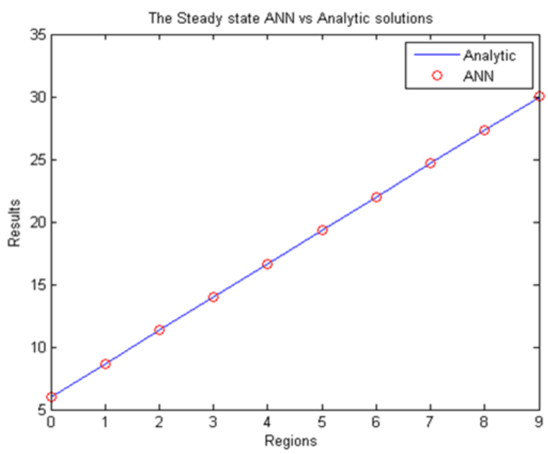

Figure 1: Steady State: - ANN vs Analytic result.

For steady state heat transfer simulation we manage to get almost perfect match between the ANN output and the analytic solutions. We divide our problem to 10 check points and following figures shows the results and the errors.

The errors graph shows significant match between the analytic results and our ANN.

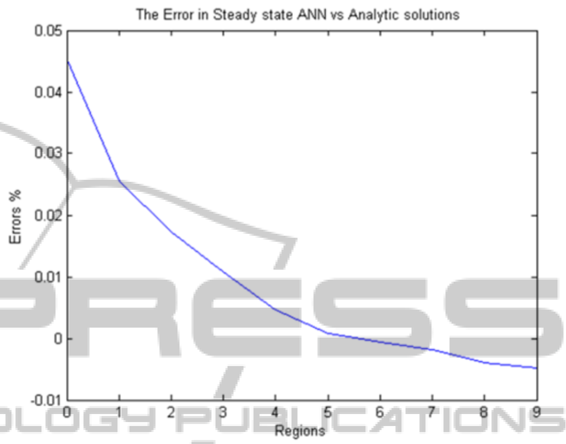

Figure 2: Steady State:- Errors percentage.

For computations cost analysis we calculate the time response for each methods. Although it is possible to measure performance using the `cputime` function, MATLAB suggest the use of `tic` and `toc` functions for this purpose exclusively.
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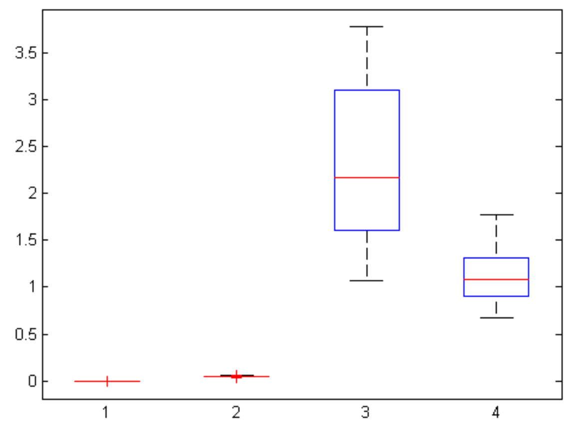

Figure 3: Time response for each Numerical methods.

The following table shows the time performance in seconds for each methods.

Table 1: The Analysis of ANN Performance.

Analytic	ANN	Crank–Nicolson method	Implicit Method
0.000024	0.038119	3.77518588	1.33223522
0.000016	0.044691	3.60739191	0.71496448
0.000017	0.052277	3.49266863	1.35002134
0.000016	0.051744	1.95030985	1.28812227
0.000016	0.05467	1.21223425	1.15282111
0.000016	0.049609	2.88919158	1.55687154
0.000015	0.050025	3.66721568	1.03937439
0.000015	0.049784	1.79117658	1.76835897
0.000015	0.055496	2.11929139	1.11576155
0.000018	0.047998	1.06746621	0.75143811
0.000015	0.052205	2.21027928	0.68007404
0.000016	0.057457	1.47667452	0.83393107
0.000016	0.056249	2.62565862	1.26190596
0.000016	0.061392	2.71878543	1.01751283
0.000017	0.047199	1.39021429	1.14600119
0.000016	0.051444	1.94558414	1.71127878
0.000017	0.049175	1.46224371	0.98020747
0.000017	0.049095	3.31138490	0.76387218
0.000015	0.047646	1.74084605	1.00064168
0.000015	0.049683	2.27498510	1.05551031

3.2 Transient Heat Flow

Our goal is to calculate the Temperature after t seconds when we consider the heat problem

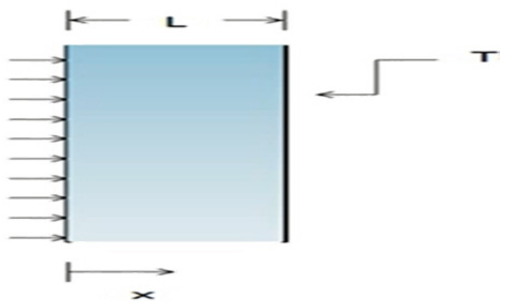

Figure 4: 1D Transient Heat problem.

The parabolic partial differential equation can describe the transient heat flow in the simplest way we get:

$$\rho C_p \frac{\partial U}{\partial t} = k\left(\frac{\partial^2 U}{\partial x^2} + \frac{\partial^2 U}{\partial y^2}\right) \qquad (1)$$

The boundaries conditions

$$u(t,0,y) = T_0, \quad u(t,L,y) = T_L \qquad (2)$$
$$u(t,x,0) = T_0, \quad u(t,x,H) = T_H$$

The initial conditions

$$u(0,x,y) = f(t = 0, x, y$$

The ANN training data is generated by find the analytic solution (variable separations. Two more numerical solution is obtained from finite difference Crank–Nicolson method and implicit scheme.

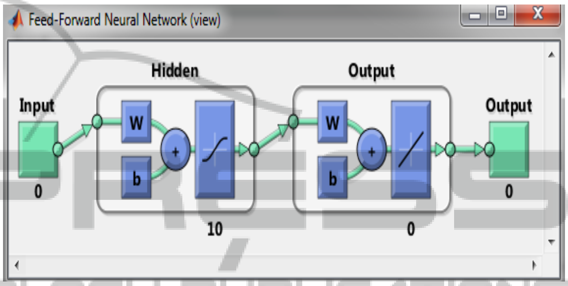

Figure 5: ANN default model.

The ANN using MATLAB Feedforward neural network with network training function that updates weight and bias values according to Levenberg-Marquardt optimization. The result shows significant errors especially when the nonlinearity appears

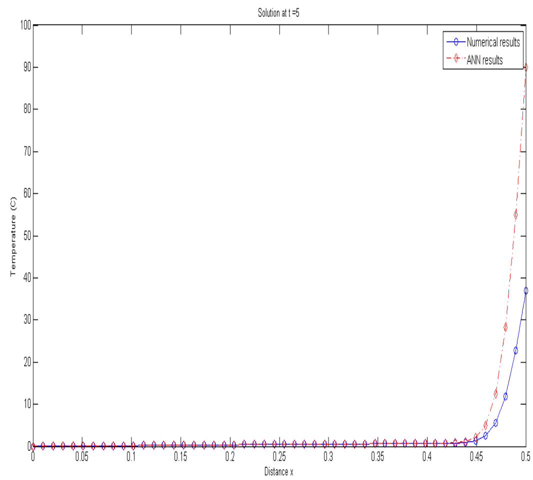

Figure 6: Transient Flow: - ANN vs Analytic result.

And the error graph

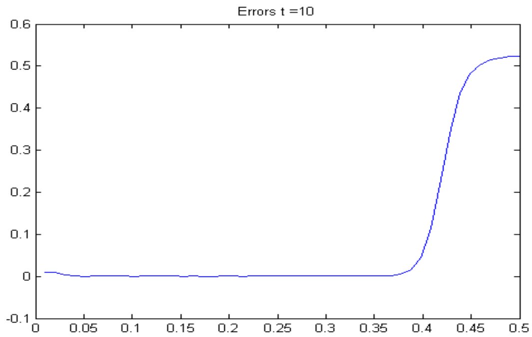

Figure 7: Transient flow: - Errors percentage.

To investigate the geometrical boundaries effects we add new input to the ANN model and train in the same previous conditions.

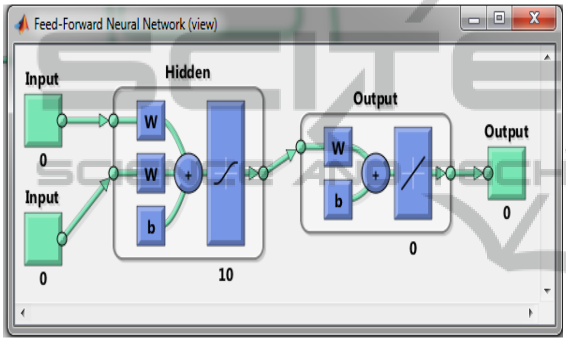

Figure 8: ANN model with geometrical boundaries inputs.

The results change with much less error percentage

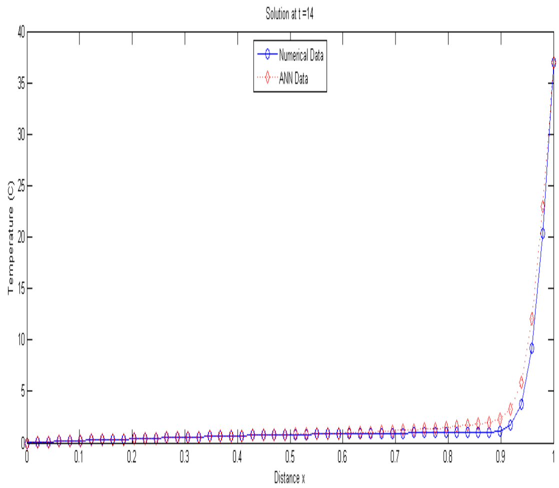

Figure 9: Transient & geometrical: - ANN vs Analytic.

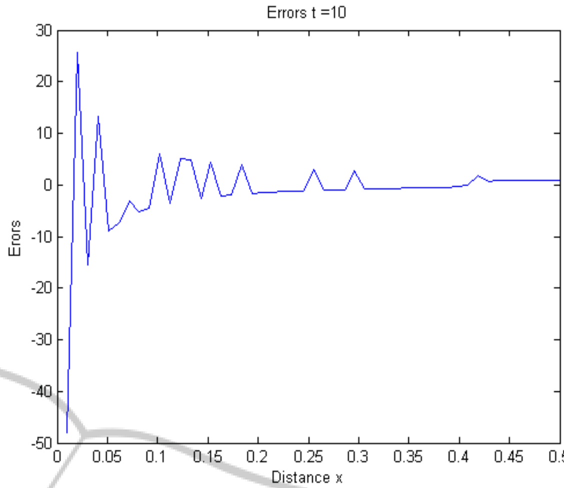

Figure 10: the errors with geometrical boundaries input.

The performance analysis wan not execute yet.

4 CONCLUSIONS

A novel ANN approached to simulate the fluid behaviour was proposed. We successfully manage to get acceptable results for heat transfer model both the steady state and transient.

Our ANN approach is fast, simple and efficient for fluid heat flow prediction. We able to investigate the effect of the geometry with known boundaries velocity. Our outcomes are acceptable for 1D-flow equations with respect to both energy and momentum equations. The ANN approach is able to handle fluid flow prediction with known boundaries velocity. This approach can be the first step for neural network computational program that can tackle variance type of problems.

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