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Modeling of Dimpled Plate Heat Exchanger Using Neural Networks

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Abstract: This paper presents neural network modeling of dimpled plate heat exchanger using neural network time series tool. In order to construct a neural network model for the heat exchanger, the input-output data of the heat exchanger is considered where the output variable is the outlet temperature of cold fluid and the input variables is the mass flow rate of hot fluid. In this work, an approach based on Nonlinear Auto Regressive with exogenous input (NARX) type model was developed using data collected from the CFD (Temperature and mass flow rate of cold and hot fluid). It was perceived that the Root Mean Square Error during training and validation stages proving that the modeling approach employed in this work is appropriate to capture the characteristics of complex and nonlinear the heat exchanger.

Key words: Dimpled plate heat exchanger · Neural network · Nonlinear Auto Regressive with exogenous input

INTRODUCTION

A dimpled plate heat exchanger is a type of heat exchanger in which surface of the metal plain plates is modified with hemispherical shaped dimples to transfer heat between two fluids. The major advantage of using dimpled plate heat exchanger is that, in which the fluids are exposed to a much larger surface area because of the dimples. This simplifies the transfer of heat, and greatly increases the speed of the temperature change. Use of dimples for heat transfer enhancements are turbine blade cooling, tube heat exchangers in chemical and textile industries, car radiators etc [1].

Computational fluid dynamics (CFD) is a subdivision of liquid mechanics that utilize numerical exploration and calculations to solve and analyze problems that involve fluid flows. PCs are utilized to play out the counts required to simulate the collaboration of fluids and gasses with surfaces characterized by boundary conditions.With rapid supercomputers, better arrangements can be accomplished. Continuous exploration yields programming that enhance the precision and pace of complex simulation situations, for example, transonic or turbulent streams.

The nonlinear autoregressive system with exogenous inputs (NARX) is a repetitive element system, with feedback connections encasing a few layers of the system. The NARX model depends on the linear ARX model, which is normally utilized as a part of time-series modelling [12]. Several authors have also used neural network as an alternative modelling method for the prediction of fouling [3-10]. Multi-Layer Perception (MLP) neural networks with Nonlinear Auto Regressive with exogenous input (NARX) structure was used to model a heat exchanger in refinery CPT [2]. The defining equation for the NsARX model is.

$$y(t)=f(y(t-1), y(t-2),\dots, y(t-n_y), u(t-1), u(t-2), \dots, u(t-n_u))$$

where the next value of the dependent output signal y(t) is relapsed on past estimations of the output signal and past estimations of an autonomous (exogenous) input signal. There are numerous applications for the NARX system. It can be utilized as a predictor, to anticipate the next value of the input signal. It can likewise be utilized for nonlinear filtering, in which the target output is a noise free form of the information signal. The utilization of the

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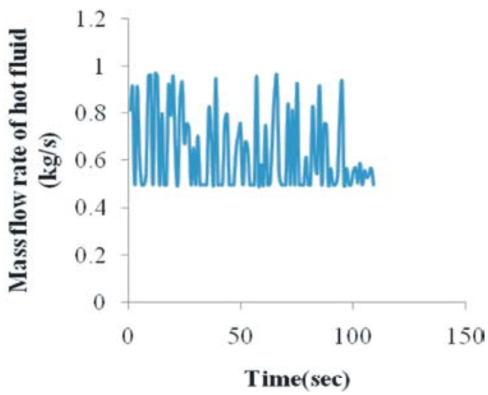

Fig. 2.1: Random Signal of Mass Flow Rate of Hot Fluid

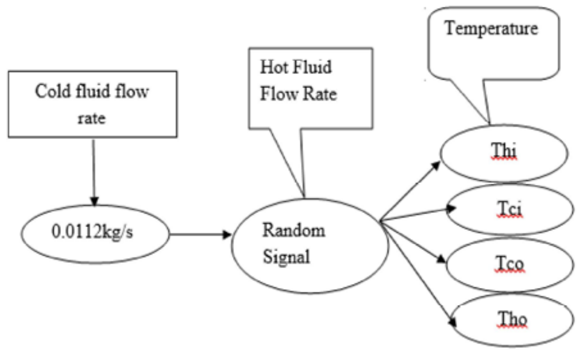

Fig. 2.2: Simulation Plan

NARX system is appeared in another essential application, the modelling of nonlinear dynamic systems [11, 12].

Simulation Plan: Simulation data was collected by setting cold fluid (Xanthum gum solution) flow rate as 0.0112kg/s, by varying hot fluid (water) flow rate, keeping inlet temperature of both fluids constant. Random input was used as hot fluid flow rate as shown in Figure 2.1

After the solution converged, transient response of cold fluid outlet temperatures were noted down till it reaches a steady state using FLUENT 15.0. Simulation plan is shown in Figure 2.2.

Simulation Procedure: In order to simulate, the following procedure has to performed.

- Start the FLUENT with 3D solver
- Read an existing grid file and feed into FLUENT
- Check the grid (e.g., concerning the dimensions of calculation domain, the cell volume, the number of nodes and area of each cell)
- Choose the suitable type of solver:

Fluent supplies three types of solver for solving the discrete equation. Basically, the specific characteristics of the investigation (incompressible and mildly compressible flows) are dealt with "segregated solver". This solver solves the continuity, momentum, energy and species equations sequentially (i.e., segregated from one another) while the other two solvers solve these equations simultaneously (i.e, coupled together) as applied for compressible flow. Here segregated solver has been selected.

- Retain the default selection of Transient from the time list.

Choose the Model: To calculate the flow field, select the k-ϵ, set Realized wall function. For coupling heat transfer (convection and conduction), activate the energy equation.

- Define the properties of following material:
  - Test fluid
  - Stainless steel material

- Define the boundary conditions
  - Cold fluid inlet flow rate
  - Hot fluid inlet flow rate
  - Cold fluid inlet temperature
  - Hot fluid inlet temperature
  - Thickness of plate

- Define the control parameter

  The following under relaxation factor are set.
  - Pressure = 0.3
  - Body force = 1
  - Density = 1
  - Momentum = 0.7
  - Turbulent kinetic energy = 0.8
  - Turbulent dissipation rate = 0.8
  - Turbulent viscosity= 1

- Select the reference of discrimination of differential equations,
  - For pressure choose PRESTO
  - For momentum choose first order upwind
  - Turbulent kinetic energy choose first order upwind
  - Turbulent dissipation rate choose first order upwind

- Set the convergence criteria,

Continuity = 0.001 K = 0.001

ϵ = 0.001

x, y, z velocity = 0

- Initialization of iterations
- Calculate the solution
  - Time step size =10(sec)
  - Maximum iterations/time step =500

Development of Narx Model in Matlab: MATLAB neural network time series prediction tool is used for developing NARX model. It includes the process of giving input variables as training data and testing data. The algorithm used is set as Levenberg-Marquardt algorithm. The transfer function chosen in this case is sigmoid transfer function in hidden layer and a linear transfer function in the output layer. Import input parameters and targets into ntstool and set the number of hidden neurons and number of delays. The neural network model thus formed is trained; the training is stopped when the number of validation checks reaches 5 [13].

RESULTS AND DISCUSSION

CFD Simulation Results of Plate Heat Exchanger: Simulation runs were performed by varying mass flow rate of hot water as random input shown in Figure 2.1 and mass flow rate of Xanthum gum solution as 0.0112 kg/s with initial temperature of cold fluid 303K and 353K for hot fluid. Outlet temperatures of cold fluid data getting from ANSYS FLUENT 14.0 were noted. These data's were used to develop Neural Network Model.

Xanthum gum solution with density 979.206 kg/m^3, viscosity 0.3Pa.s, thermal conductivity 1.767 W/m K, specific heat capacity 4118.78J/kg K was used as cold fluid with initial temperature 303K.Water with density 880.544kg/m^3, viscosity 0.00057Pa.s, thermal conductivity 0.659 W/m K, specific heat capacity 4214.95 J/kg K [Muthamizhi, 2014] was used as hot fluid with initial temperature 353K. Random input (Figure 2.1) between 0.5 to 1 LPM was used as mass flow rate of water solution.

It can be observed (Figure 5.1) that outlet temperature of Xanthum gum solution increases with increase in mass flow rate and decreases with decrease in mass flow rate of hot fluid (water). After 950 seconds outlet temperature of cold fluid started to reach steady state and at 1080 seconds it reaches a temperature of 322.59 K, that is it completely attained a steady state.

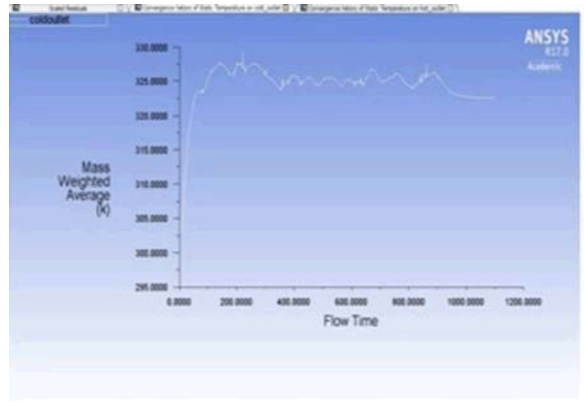

Fig. 5.1: Outlet Temperature of Xanthum Gum Solution Versus Time

Table 5.1: Results Obtained from Neural Network Time Series Tool

Number of Hidden neurons	10
Number of delays,d	4
MSE for Training	0.04384
MSE for Validation	0.012527
MSE for Testing	0.0158254
R for Training	0.988582
R for Validation	0.981608
R for Testing	0.914469

Neural Network Model of Plate Heat Exchanger: In order to construct a neural network model for the heat exchanger, the input-output data of the heat exchanger is considered where the output variable is the outlet temperature of cold fluid and the input variables is the mass flow rate of hot fluid [10].

In this study the mass flow rate of cold fluid is kept constant (0.0112Kg/sec). NARX model was generated by varying the number of neurons in the hidden layer and number of delays based on R value. NARX model proposed using neural network time series tool (ntstool) in MatlabR2013a is shown in Table 5.1.

Figure 5.2 displays the error autocorrelation function. It depicts how the prediction errors are connected in time. For an impeccable forecast model, there should be only one nonzero value of the autocorrelation function, and it ought to happen at zero lag. This would imply that the prediction errors were totally uncorrelated with each other .On the off chance that there was critical relationship in the prediction errors, and then it ought to be conceivable to enhance the forecast - maybe by increasing the number of delays in the tapped delay lines. For this situation, the connections, aside from the one at zero lag, fall roughly inside the 90% certainty limits around zero, so the model is by all accounts sufficient.

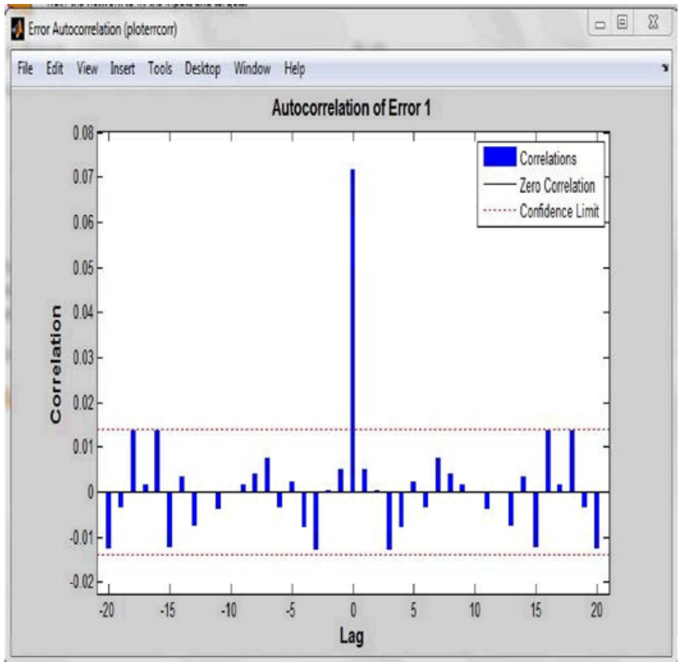

Fig. 5.2: Autocorrelation of Error

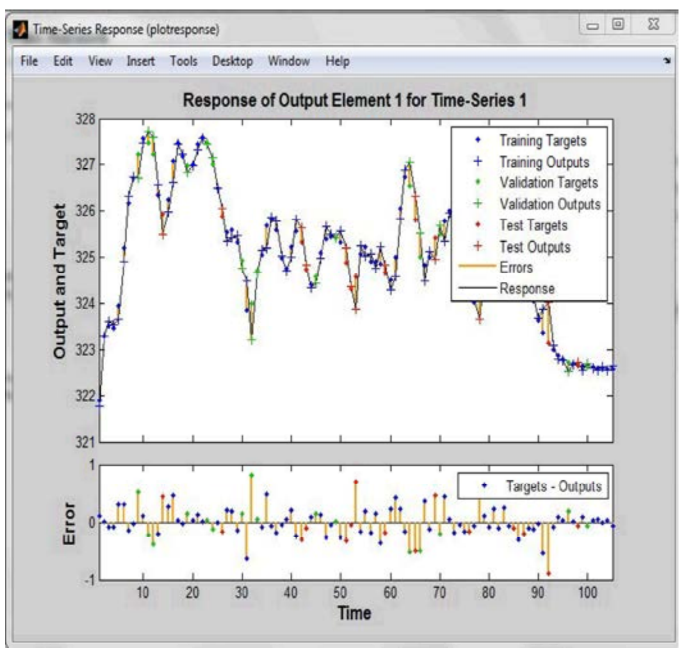

Fig. 5.3: Response of Output Element for Time Series

Figure 5.3 showcases the outputs, targets and error versus time. It likewise shows which time focuses were chosen for training, testing and validation. Figure 5.4 represents the input-error cross-correlation function. Input-error cross-correlation function outlines how the errors are corresponded with the input sequence x (t).

For a perfect prediction model, the majority of the correlation ought to be zero. On the off chance that the input is associated with the error, then it ought to be conceivable to enhance the prediction, maybe by increasing the number of delays in the tapped lines. For this situation, all of the relationships fall inside the confidence limits around zero.

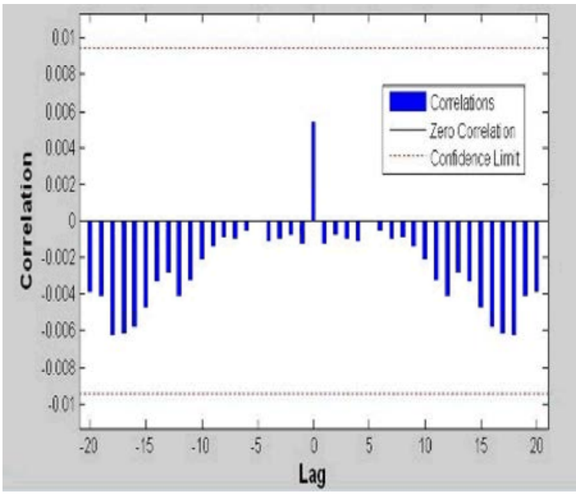

Fig. 5.4: Correlation between Input and Error

Heat exchanger is a profoundly nonlinear process; in this manner, a nonlinear prediction method, e.g. neural network based strategies, ought to be a superior match in a predictive control methodology.

CONCLUSIONS

Transient response of plate heat exchanger was found out. For that mass flow rate of hot fluid (water) has generated as random signal in Mat lab. Keeping the mass flow rate of cold fluid (Xanthum gum solution) as 0.0112 kg/s with initial temperature of cold fluid 303K and 353K for hot fluid, outlet temperatures of cold fluid data getting from ANSYS FLUENT 14.0 were noted. In order to construct a neural network model for the heat exchanger, the input-output data of the heat exchanger is considered where the output variable is the outlet temperature of cold fluid and the input variables is the mass flow rate of cold fluid. A multilayer perception neural network with 10 neurons in the hidden layer and number of delays 4 was used. Regression value, R for Training = 0.998, Testing = 0.914 and Validation = 0.982. The correlations, except for the one at zero lag, fall approximately within the 90% confidence limits around zero in auto correlation error graph, so the model seems to be adequate. Heat exchanger is a highly nonlinear process; therefore, a nonlinear prediction method, e.g. neural network based methods, should be a better match in a predictive control strategy.

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