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Thermal Performance Analysis of Shell and Tube Heat Exchanger

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Abstract- The design and prediction of heat exchanger behaviour are too complicated to mathematically mode land solve using analytical solution. Closed form solutions are available only in situations where the model has several simplifying assumptions. Heat exchanger design based on these assumptions has errors that make the prediction of thermal behaviour challenging. In this study shell and tube heat exchanger with 10 different baffles are placed along the shell in alternating orientations with cut facing up, cut facing down, etc., in order to create flow paths across tube bundle. The geometric modelling is done using CAD software called CATIA V5R21 because it is easy to model Heat exchanger in 3D modelling software.

Keywords- Shell and tube heat exchanger, design, baffles.

I. INTRODUCTION

Heat exchangers are also used to transfer heat between two fluids that would be at various temperatures along a solid surface. The nonlinear dynamics of this process, notably the varying steady-state gain or time constant with process fluid [1], make it complicated. The shell-and-tube heat exchanger is the most popular form of heat exchanger, with uses in refrigeration, power production, heating, air conditioning, chemical processes, manufacturing, and medicine [2]. It really is made up of a bundle of tubes contained in a cylindrical shell, including one fluid flowing thru the tube and another running between both the tubes as well as the shell.

A heat exchanger may be defined as a device that transmits thermal energy between two or more fluids of varying temperatures. Several industrial processes would indeed be impossible to complete without this equipment.

Refrigeration, air conditioning, and chemical plants all use heat exchangers. It's utilized for a variety of things, including transferring heat from a hot to a cold fluid. They're commonly employed in a variety of industrial settings. Researchers had worked on a variety of projects in attempt to increase performance.

The velocity and temperature contour fields upon that shell side, on the other hand, are much more complicated, and their performance is influenced by baffle elements such as their arrangement the spacing scheme.

Round tubes were put in cylindrical shells having their axes aligned with the shell axis to create this. Shell side refers to the region surrounding the tubes, whereas tube side refers to the inside tubes. The primary function of baffles would be to produce turbulence, which increases the convective heat transfer coefficient of the shell side fluid.

The following methods are used to evaluate the performance of the heat exchanger: I Outlet temperature of the hot stream (Tho) profile, ii) Approach temperature (Tho - Tci) profile, iii) Log Mean Temperature Difference (LMTD) with time, iv) Heat load profile, and v) Time series of overall heat transfer coefficient.

The first four approaches are commonly utilized, however they are poor at distinguishing the net effect of fouling of process disturbances. The total heat transfer coefficient technique, on the other hand, necessitates comprehensive computations and knowledge of the exchanger shape [3].Fouling causes the heat exchanger's performance to decrease over time. It tends to rise with time, with a particularly site-specific trajectory. As both a result, a predictive model of evaluating heat exchanger performance is required.

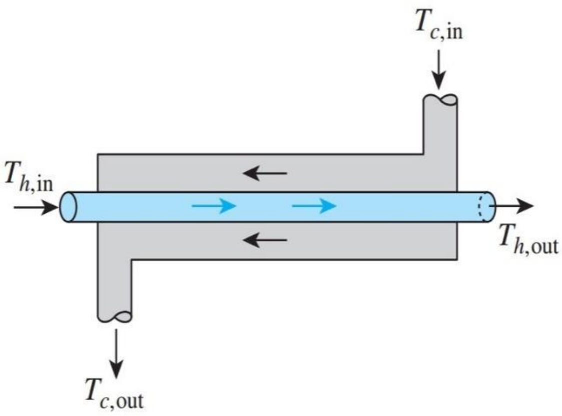

Fig 1. Double pipe heat exchanger.

II. REVIEW OF PAST STUDIES

Sundaram et al (2016) examine the prediction of a outlet liquid temperature of a saturated steam heat exchanger from its liquid flow rate, 4 distinct neural networks are considered: Elman Recurrent Neural Networks (ERNN), Time Delay Neural Networks (TDNN), Cascade Feed Forward Neural Networks (CFFNN), and Feed Forward Neural Networks (FFNN). To train, validate, and evaluate the performance of each neural network model, a benchmark dataset of 4000 tuples is employed.

Shrikant (2016) the impacts of various baffle designs on the heat transfer coefficient and pressure drop in a shell and tube heat exchanger (STHX) were investigated. The use of baffles in shell and tube heat exchangers improves heat transmission while simultaneously increasing pressure drop. SOLID WORKS Flow Simulation software is used to design shell and tube heat exchangers featuring single, double, triple segmental baffles, helical baffles, and flower baffles, as well as fluid dynamic simulations (ver.2015). Simulation studies revealed how single segmental baffles had the highest heat transfer coefficient, pressure drop, or heat transfer rate for much the same shell side mass flow rate.

Kamble et al (2014) The use of artificial neural network (ANN) modelling in different heat transfer applications, such as constant and dynamic thermal issues, heat exchangers, gas-solid fluidized beds, and so forth, was examined. Several crucial issues in thermal engineering cannot always be solved using typical analysis methods such as basic equations, conventional correlations, or trial and error to build unique designs from experimental data. The use of the ANN tool using various methodologies and structures reveals that the findings provided using ANN and experimental data are in good agreement.

The aim of this paper is to highlight current improvements in ANN and how it has been successfully used to a number of key heat transfer challenges. According to the literature, the feed-forward network with back propagation approach has been effectively utilized in various heat transfer investigations.

Kwang-Tzu Yang (2008) The goal of this work is to showcase recent advances in ANN and how it has been effectively applied to a variety of major heat transfer problems. The feed-forward network incorporating back propagation technique has already been successfully used in many heat transfer experiments, per the literature.

Singh et al. (2011) The performance of three training functions (TRAINBR, TRAINCGB, and TRAINCGF) utilized for training NN to forecast the value of the specific heat capacity of both the working fluid, LiBr-H2O, employed in a vapour absorption refrigeration system were evaluated. The percentage relative error, coefficient of multiple determination, RMSE, and sum of a square owing to error were employed as comparison metrics.

The input parameters include vapour quality and temperature, with specific heat capacity as being one of the output parameters. The training is maintained until the least mean square error (MSE) at a specific number of epochs was found. The TRAINBR function outperformed the other two training functions based on findings of performance parameters.

Gerardo Diaz et al (2001) Apply the artificial neural network (ANN) approach to the modelling of a heat exchanger's time-dependent behaviour and use it to manage the temperature of air travelling through it. Inside an open loop test facility, the tests are carried out. To begin, an approach for training and predicting the dynamic behaviour of thermal systems including heat exchangers was provided. Then, using two artificial neural networks, somebody to mimic the heat exchanger the other as a controller, an internal model strategy for controlling the over-tube air temperature is devised. To avoid a steady-state offset, an integral control is performed in tandem with the neural network controller's filter. The findings correspond to PI and PID controllers that are commonly used. The neural network controller has less oscillating behaviour, allowing the system to attain steady-state operating conditions in areas where the PI and PID controllers are not quite as effective.

Ahilan C et al (2011) artificial neural networks are used to construct a prediction model for shell and tube heat exchangers (ANN). The trials are carried by using a full factorial design of experiments to construct a model utilizing input parameters including such hot fluid intake temperature or cold and hot fluid flow rates. The total heat transfer coefficient of such a heat exchanger, which itself is utilized for performance evaluation, is the output parameter.

ANN model was educated and trained to use a feed forward back propagation neural network. Through comparing the ANN findings to the experimental data, the constructed model is validated and evaluated. It demonstrates that perhaps the model and the results are in good agreement.

Jasim (2013) Heat transfer study of shell-and-tube heat exchangers, which are frequently used in power plants and refineries, was performed using an Artificial Neural Network. To train & test networks, the Back Propagation (BP) technique was employed, which separated the data into three samples (training, validation, and testing data) to provide more approach data from genuine cases. Inlet water temperature, inlet air temperature, or air mass flow rate are all inputs to the neural network.

In ANN, two outputs were collected (exit water temperature to cooling tower & exit air temperature to second phase of air compressor). To train the classifier, the reference heat exchanger model provided 150 sets of data on different days.

Regression between the planned goal and the predicted outcome For training, validation, testing, as well as all samples, the ANN output shows that the values are fairly equal to one (R=1). A total of 50 sets of data were gathered to test the network and compare the intended and predicted exit temperatures (water and air temperatures).

Maheshwari (2018) artificial neural networks were used to assess the performance of a parallel flow heat exchanger (ANNs). Experiments were carried out utilizing a complete factorial design of experiments to construct a model employing characteristics such as temperatures, capacity ratio, and optimal NTU constant value. A feed forward back propagation neural network is used to construct and train an ANN model regarding efficiency, entropy generation number, and total heat transfer coefficient multiplied by the area of a theoretical/clean heat exchanger.

Through comparing the findings to the experimental results, the generated model is verified and evaluated. This model is used to evaluate the heat exchanger's performance in the real/foulled system. It helps the system enhance its performance through maximizing asset usage, conserving energy, and lowering production costs.

Amlashi (2013) Applied an artificial neural network model to the nonlinear identification of a liquid saturated steam heat exchanger (LSSHE). Heat exchangers are nonlinear and non-minimum phase processes with changeable operating conditions. The rate of change of fluid flow into to the system is also employed as such an input variable, while experimental data collected from fluid outlet temperature measurement inside a laboratory environment has been used as an output variable. The outcomes of neural network & traditional nonlinear model identification are compared. Due to the obvious independence of the model assignment, the simulation results demonstrate that perhaps the neural network model is reliable and quicker than standard nonlinear models using time series data.

Mahdi Jalili Kharaajoo (2004) to control the dynamics of such a heat exchanger pilot plant, I created a neural network-based prediction model. Because a heat exchanger is just a nonlinear process, a nonlinear prediction approach may be a good fit for just a predictive control strategy.

The benefits of neural networks in process modelling are investigated, and a neural network-based predictor was created, trained, and evaluated as part of the predictive controller. A Multi-Layer Perceptron (MLP) neural network is used to determine the plant's dynamics. After that, a predictive control method based here on plant's neural network model is used to accomplish set point tracking of the output. Using simulation tests, the suggested controller's performance by comparing with that of Generalized Predictive Control (GPC). The obtained results show that the proposed method is both effective and useful.

Ricardo (2014) A counter-flow concentric pipes heat exchanger featuring R134a refrigerant flowing within the circular part and temperature regulated warm water travelling through the annular section was used during the experiments. The development of an inverse Rankine refrigeration cycle including measuring devices, sensors, and a data collection system to collect experimental measurements under various operating circumstances too was part of this project. Various neural-network configurations were trained using some of the data.

The best neural-network model is now being used to make predictions, and the results were compared to experimental data that had not been utilized for training. The findings of this study show that artificial neural networks may be used as accurate forecasting tools in calculating convective heat transfer rates during evaporative processes.

A.R. Moghadassi (2011) for the examination of Shell and Tube Heat Exchangers, a novel approach based here on artificial neural network (ANN) was presented. The relevant experimental data was acquired from Kern's book, TEMA, and Perry's handbook, as well as special parameters for heat exchangers analysis was created using a neural network. Back-propagation learning algorithm with Levenberg-Marquardt training technique was utilized in this study. The trained networks' accuracy and trend stability were tested using their abilities to predict unknown data.

The error restriction was set at 10-3-10-6 using MSE error assessment. Parameters can be calculated without the need of charts, tables, or sophisticated formulae. Twenty-two networks have been used in this study to model a variety of features. The outcomes revealed the ANN's capacity to anticipate the outcome of the analysis.

Thirumarimurugan (2009) for different flow rates, engaged in determining the exit temperature from both cold and hot fluid. The overall heat transfer coefficient (U), effectiveness(), cold side efficiency(c), and hot side efficiency(h) of plate type heat exchangers were determined using the water-water system, water-acetic acid system, water-ethylene glycol system, water-toluene system, as well as water-kerosene system at 9 percent, 10 percent, 20 percent, and 25 percent composition (h).

The general regression neural network (GRNN) model was utilized to create neural networks utilizing this experimental data. Furthermore, these networks was evaluated using a set the testing data, as well as the simulated results was compared with the actual testing data results, and it has been discovered that now the experimental data as well as the simulated data are quite similar.

Kumra et al (2013) the support vector machine model was used to forecast the rate of heat transfer of a wire-on-tube type heat exchanger. The heat transfer rate for heat exchangers has already been determined using a variety of methods. MATLAB software was used to create a computer programmed to solve the method. This aided us in formulating a complete heat transfer equation with minimal inaccuracy as compared to traditional techniques. Various applications of the structural risk reduction concept in cost function formulation and quadratic programming in model optimization, that model has intrinsic benefits. There seems to be a comparison here between artificial neural network as well as the support vector machine approaches.

III. RESEARCH METHODOLOGY

First the geometry of the model is created in CATIA V5R21. The model is saved in IGS format. The external geometry file is imported in the design modeller of the ANSYS fluent. The geometry has totally 22 parts. One shell and 21 tubes bundle. In free meshing a relatively coarse mesh is generated. It contains both tetrahedral and hexahedral cells having triangular and quadrilateral faces at the boundaries. Later, a fine mesh is generated using edge sizing. In this, the edges and regions of high pressure and temperature gradients are finely meshed.

Different boundary conditions were applied for different zones. Since it is a shell-and-tube heat exchanger, there are two inlets and two outlets. The inlets were defined as velocity inlets and outlets were defined as pressure outlets. The water inlet boundary conditions are set as Flow opening inlets and outlet boundary conditions are set as Pressure opening outlets. The exterior wall is modelled as adiabatic. The simulation is solved to predict the heat transfer and fluid flow characteristics by using k-ε turbulence model.

Shell side inlet is set as flow opening the mass flow rate of water varied from 0.7533 kg/s for different simulations and temperature is set to 303 K. Tube side inlet is set to flow opening the mass flow rate of graphene nanoparticles and water is varied from 0.7 kg/s to 1.2 kg/s and the temperature is set to 363 K.

IV. RESULTS AND DISCUSSION

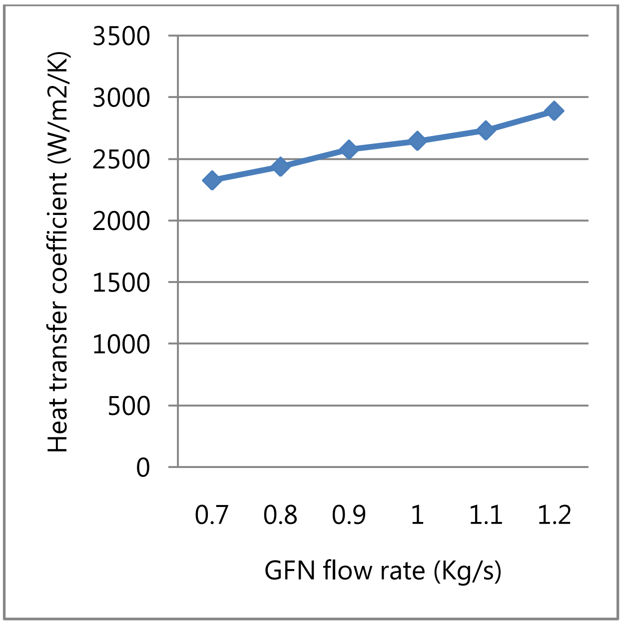

Fig 2. Variation of heat transfer coefficient in STHX with single segmental baffle

Fig. 1, shows the variation in heat transfer coefficient for different baffle configurations. The slope of the curves is generally found to decrease with increase in shell side mass flow rate.

Fig. 2 shows the variation in shell side pressure drop for different baffle configurations. The slope of the pressure drop is found to increase with increase in mass flow rate. More the mass flow rate, steeper is the curve profile. Single segmental baffles show the highest pressure drop while flower ‘A’ type baffles show minimum Pressure drop.

From fluid dynamics, a boundary layer develops at the channel wall, which insulates the centre of the fluid from the heat transfer surface. This decreases the rate of heat transfer. Conversely, if the flow continuously meets resistance, it is effectively stirred. This enables a larger amount of the flow to directly contact the heat transfer surface earlier in the flow path.

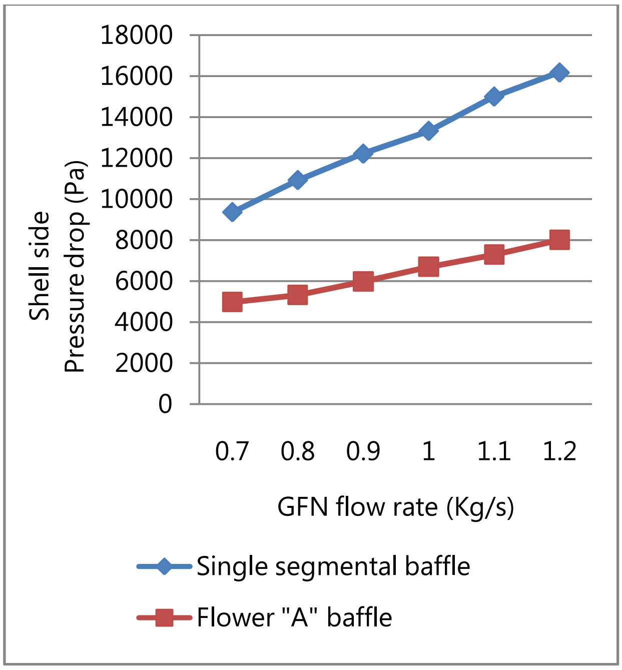

Fig 3. Variation of pressure drop with parameters in STHX with Flower ‘A’ baffle.

V. CONCLUSION

CFD simulation studies on Shell and Tube Heat Exchanger has been carried with single, flower ‘A’ type, and flower ‘B’ type baffle configurations.

The following are the conclusions arrived from these simulation studies:
From simulation, it is inferred that the flow pattern created is similar to that created by flower ‘A’ baffle, except that more stream lines are observed in flower ‘A’ baffles when compared with flower ‘B’ baffles and hence lesser is the stagnation zone in flower ‘A’ when compared with flower ‘B’ baffle. Whereas in flower ‘A’ fluid velocity magnitude on the shell side changes periodically in the central part of the flower ‘A’ baffled heat exchanger.

When the fluid passes a baffle, it is firstly accelerated rapidly and then flows across the breaches with large velocity. After rushing out of the breaches, the fluid is expanded suddenly and the velocity is decreased gradually. This periodic flow pattern is caused by the periodic changes of flow area which is induced by arrangement of flower baffles. Moreover, it is also noticed that in the downstream just behind a baffle, two recirculation flow regions are generated, where the velocity magnitude is very small.

As the volumetric flow rate of the tube side fluid (GFN) is increased from 0.7533 to 0.9533 Kg/s, the overall heat transfer coefficient increased from 2211 to 2470 W/(m^2 /K). This is because increase in the volumetric flow rate increases the mass flow rate of GFN in a much faster rate than over all heat transfer coefficient or the heat energy transferred. Since the specific heat remains almost constant, tube outlet temperature should decrease to comply with law of conservation of energy. As the flow rate of tube side fluid is increased, the tube side heat transfer coefficient increases, which in turn decreases fin effectiveness and surface effectiveness.

Flower 'B' Baffles are more effective than Flower 'A' Baffles as they reduce the Pressure Drop to the same extent as that of Flower 'A' baffles but with a better thermal performance associated.

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