International Journal of Scientific Research & Engineering Trends
Volume 8, Issue 2, Mar-Apr-2022, ISSN (Online): 2395-566X

A Review on Thermal Performance Analysis of Shell and Tube Heat Exchanger

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Abstract- Shell and tube heat exchanger with single segment baffles, helical baffles at varied helix angles, and flower baffles was researched and compared in enhancing performance, according to the literature review. Furthermore, simulations involving single, double, triple segmental baffles, helical baffles, and flower baffles have not been compared using the same STHX specification and input circumstances. As a result, a unique idea was developed to investigate the impacts of multiple baffle designs in shell and tube heat exchangers (STHX), including such single, double, triple segmental baffles, helical baffles, and flower baffles, on heat transfer coefficient and pressure drop.

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 utilised 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 utilised, 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.

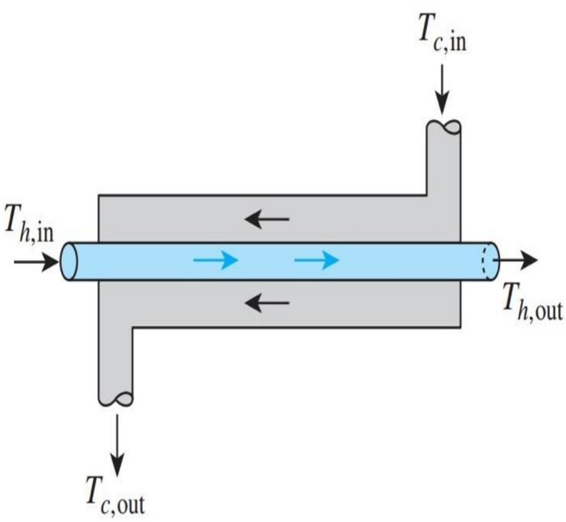

Fig 1. Double pipe heat exchanger.

II. CLASSIFICATION OF HEAT EXCHANGER

1. Nature of Heat Exchanger:

1.1 Direct contact heat exchanger: In such a direct contact heat exchanger, heat is exchanged simply mixing hot and cold fluids directly, and heat and mass are transferred simultaneously. Example: cooling tower, jet condenser, and direct contact feed water.

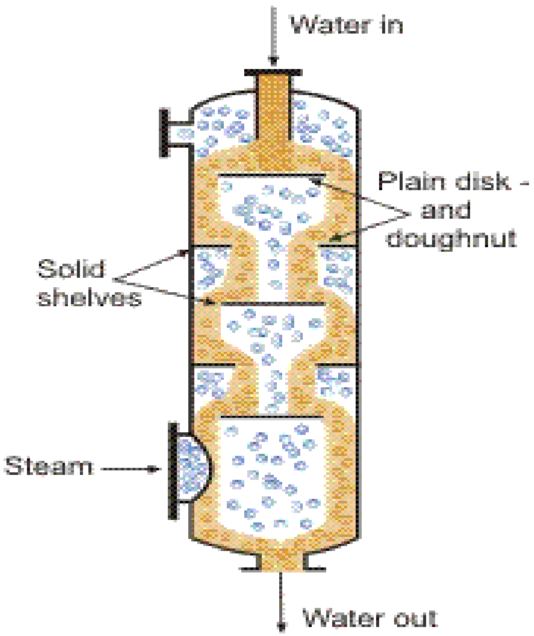

Fig 2. Direct contact heat exchanger.

1.2 Indirect contact heat exchanger: The heat transfer among two fluids might be carried out via the transmission through a wall that divides the two fluids in just this form of heat exchanger. Example: Regenerator, Recuperator.

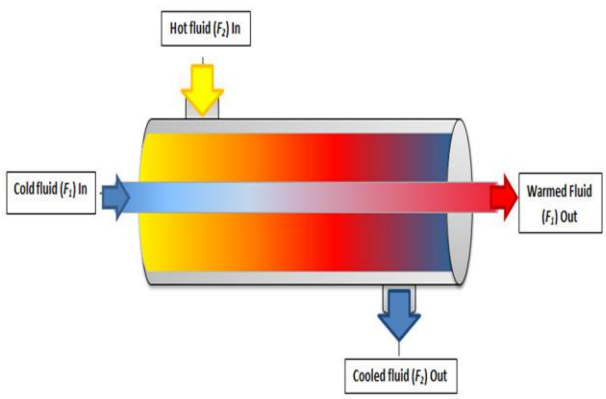

Fig 3. Indirect contact heat exchanger.

2. Based on Flow Pattern or Arrangement

2.1 Parallel flow heat exchanger: Fluids flow in the same direction in a parallel flow heat exchanger. If indeed the fluid's specific heat capacity remains constant.

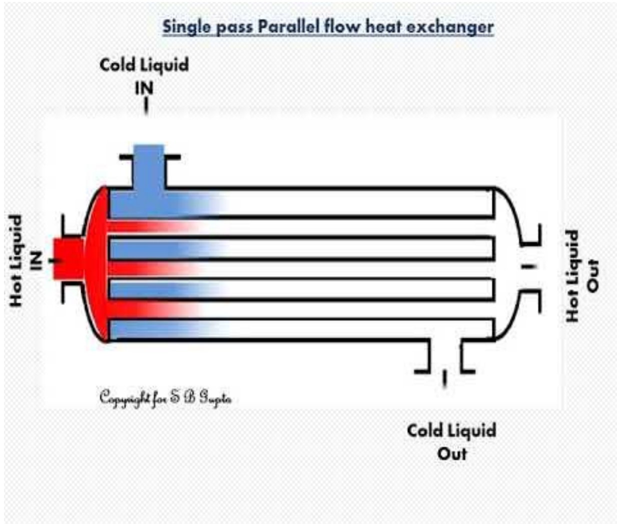

Fig 4. Parallel flow heat exchanger.

b. Counter flow heat exchanger:-Fluids move in the opposite direction in a counter flow heat exchanger. When fluids' specific heat capacities remain constant.

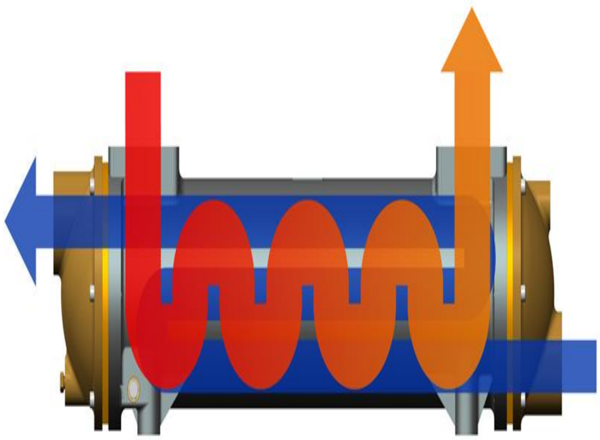

Fig 5. Counter flow heat exchanger.

c. Cross flow heat exchanger:- The direction the fluids in such a cross flow heat exchanger is perpendicular to each other.

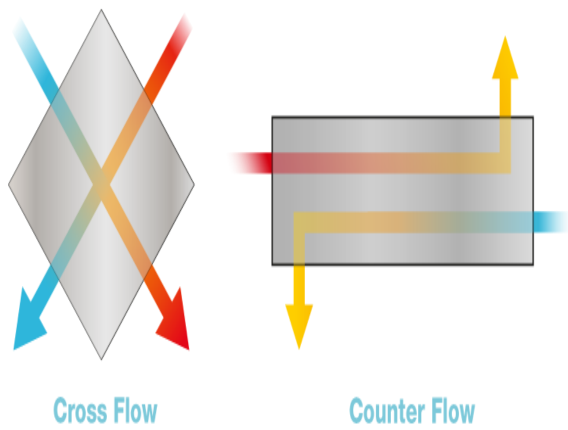

Fig 6. Cross flow heat exchanger.

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3. Design and Mechanical Construction:

3.1 Shell and tube heat exchanger: A heat exchanger with a shell and tube configuration is indeed a type of heat exchanger. This is the most frequent heat exchanger in oil refineries as well as other major chemical processes, and it's designed for greater pressures. This form of heat exchanger consists of such a shell (a huge pressure vessel) with a bundle of tubes inside it, as even the name indicates. To transfer heat between the two fluids, one fluid flows outside the tubes and another fluid flows over the tubes (via the shell). A tube bundle is indeed a collection of tubes that can be made up of several sorts of tubes, such as plain tubes, longitudinally finned tubes, and so on.

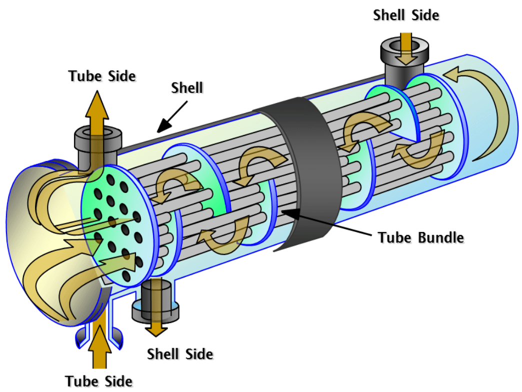

Fig 7. Shell and tube heat exchanger.

3.2 Compact heat exchanger: There really are heat exchangers that also are designed for a specific purpose and have a significant transfer surface area per unit volume of both the exchanger. Those who are often used whenever the convective heat transfer coefficient of a few of the fluids is significantly lower than for the other fluid. Example: plate fin, flattened fin tube exchanger etc.

Fig 8. Compact heat exchanger.

3.3 Concentric Tubes: Two concentric tubes have been used in the song, each conveying one of it's fluids. The flow might be parallel or anti-parallel. The heat exchanger's efficiency is improved through using whirling flow.

III. 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. SOLIDWORKS 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 utilised 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) utilised for training NN to forecast the value of the specific heat capacity of both the working fluid, LiBr-H_2O, 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 utilising 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 utilised 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 utilising 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 maximising 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 utilised 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 utilised 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 utilised to create neural networks utilising 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 programme 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.

IV. CONCLUSION

Shell and tube exchangers have been widely employed in a variety of engineering applications for decades, including chemical engineering processes, power generation, petroleum refining, refrigeration, air-conditioning, and the food sector. Especially compared to other types of heat exchangers, shell and tube heat exchangers are very easy to produce but have a wide range of applications. Shell-and-tube heat exchangers have been shown to account for more than 30% of all heat exchangers in operation.

Baffles serve an important part in the construction of Shell and Tube Heat Exchangers (STHX). They offer tube support, let the shell-side fluid flow can retain a desired velocity, and keep the tubes form wobbling. The shell-side flow is additionally guided forward through the tube bundle by baffles, boosting fluid velocity and heat transfer coefficient. Heat transfer was boosted with the most widely used single segmental baffles because the baffles direct the shell side fluid to flow inside a zigzag pattern between both the tube bundle, increasing turbulence intensity and local mixing.

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