TEACHING LEARNING OPTIMIZATION AND NEURAL NETWORK FOR THE EFFECTIVE PREDICTION OF HEAT TRANSFER RATES IN TUBE HEAT EXCHANGERS

by

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Heat exchangers are widely used in many field for the purpose of heat from one medium to another. In heat exchanger one or more fluids are used, and which are various types based on its flow and construction. Design of heat exchanger is one of the important field, in the research due to its application. In recent decade the simulation is used in most of the engineering application. A proper simulation technique can effectively analysis the functionality and behavior of any machine before its construction or production. In this sense the machine learning techniques are used in some simulation analysis to model the machine or engine. In this work we used a hybrid neural network for the modeling of shell and tube type heat exchanger and its heat transfer rate is predicted effectively. The computational performance of the proposed technique is compared with the conventional technique and it is proved the effectiveness of the hybrid machine learning technique.

Key words: *heat exchanger, ANN, heat transfer rate, hybrid machine learning, teaching learning optimization, shell and tube heat exchanger*

Introduction

The heat exchangers are widely used in automobiles, optical systems, lasers, X-ray tubes, military applications, aerospace engines, and power supplies to transfer or exchange heat [1]. Liquids like water or oil are used as a coolant to transfer heat [2]. The fluid or liquid used in the exchanger are single or two phase [3]. Then based on the type of exchanger the fluid may be in direct contact or separated. Some devices uses fired heater or nuclear fuel pins as energy sources, those devices are not considered as normal heat exchanger. But these devices also may have the same principles and designs as the normal heat exchanger [4].

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The heat exchanger has two types of approaches. The first approach is categorized based on the flow configuration in the exchanger [5]. The second type is categorized on the equipment construction. In flow type approaches, four different flows are considered: concurrent, counter, cross, and hybrid flow [6]. Then the construction type approaches are classified into two types: recuperative and regenerative. But in general, the heat exchangers are divided into two types: indirect and direct [7].

The steams in indirect heat exchangers are mostly separated by metal wall. The tube and shell exchanger is one of the most used indirect type of heat exchangers. In this type the tubes are mounted inside a cylindrical tube [8].

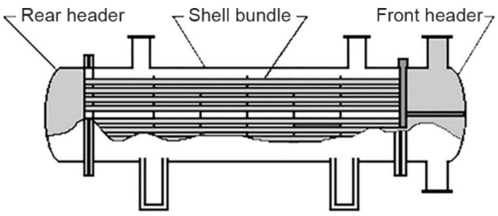

Figure 1. Tube and shell type heat exchanger

In fig. 1, the typical illustration of the shell and tube type heat exchanger is given. The structure of tube and shell heat exchanger has tubes and shells to exchange heat. Here two fluids are used to exchange the heat energy [9]. The first fluid allows to flow outside the tubes and the second fluid get flows inside or through the tubes of the exchanger. In the fluids used in this type of exchanger either single or two phases. In this type of heat exchangers, its physical body consists of four major parts: tube, rear, front, and shell [10].

The front end of the exchanger allows the fluid to enter into the tube side and the rear end leaves the fluid for the tube side. The tube bundle comprises of tube sheets, tubes, ties roads, and baffles to hold the bundle together [11]. The shell in this exchanger has the tube bundles. This is the popular type of heat exchanger, which is made up of metals and for some special type it can also made by glass, plastics, and graphite. This is a special type of exchanger, and are widely used in many applications [12].

Simulation in engineering application is widely penetrated now a days, due to its benefits these approach is followed in many filed including manufacturing [13]. Many simulation tools are available to analysis the graphical and behavior of any component and machine before producing it. It loosen the effort and cost of production, and helps to predict the performance before purchasing or producing it. So for in many research the authors have simulated many applications. But they lack to use a proper machine learning technique for prediction of machine behavior [14].

In some research the authors have effectively used the neural network for the forecasting the internal computation engine performance. But the prediction or forecasting of heat exchanger performance using machine learning technique is a challenging task. Hence in this paper, we are planned to propose a novel machine learning technique for the effective prediction of heat transfer rate of tube and shell heat exchanger. Wang *et al.* [15] have initiated this idea and presented a technique using ANN for the prediction of rate of heat transfer. But the performance of ANN is not fulfilled due to the usage of normal back propagation algorithm for the learning purpose. Thus in this paper we are using a teaching learning optimization (TLO) of the effective learning and reduce the learning error. The proposed technique is tested using the experimental data used in [15].

Problem formation

The major objective of the proposed work is to develop a better technique for the effective prediction of heat transfer rate using machine learning technique. Thus the machine learning technique modeled as the shell and tube. In this work we are using ANN as the machine learning technique. Then TLO is used to train the ANN. Thus we formulate the learning error of the ANN as the problem or objective function, which is reduced by employing the TLO. The objective function is given:

$$BP_{\text{error}} = \sum_{k=1}^{Z} \partial_k \tag{1}$$

where BP_{error} is the mean square error or back propagation error, and ∂_k – the learning error rate of kth training data set of the heat exchanger.

In following text the procedure using ANN and TLO for the error reduction is given.

Experimentation and data collection

In this work we used the data presented in [15]. In the referred paper, the authors described an experimentation, which is briefly described in this section. In the experimentation two heat exchangers which were named HX1 and HX2. The first heat exchanger is made with segmental baffles and is shown in fig. 2. The second exchanger is made with continuous helical baffles and its schematic is shown in fig. 3 [15].

Figures 2 and 3 show the two heat exchangers, one only difference between these two devices are its baffles type and the helical baffles has the middle in middle out is followed in first exchanger and the side in side out is followed in second exchanger. In both the type of heat exchanger the cold water allowed to flows in tube side and the hot oil allowed to flows in the shell side. These exchangers has two blocked centre tubes. Moreover the geometrics parameters are varied to collect the different data. The geometric parameters considered in this work are total tube number N_t, baffle pitch S_b, total baffle number N_b, and center diameter D_c.

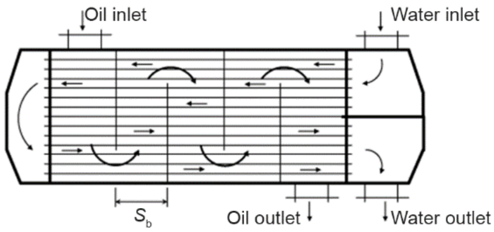

Figure 2. Schematic of segmental baffles based heat exchanger

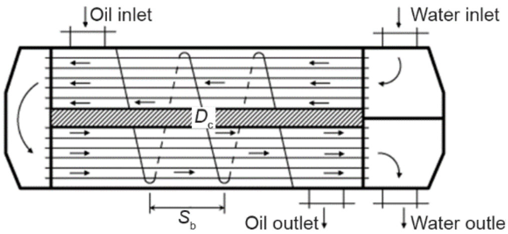

Figure 3. Schematic of continuous helical baffles based heat exchanger

These experiments were executed as per the Reynolds number in the shell side between 300 and 7000. Then in the tube side the Reynolds number was considered in the range between 3000 and 4000. Then the heat transfer rate varied from 20 kW to 50 kW. Totally 39 sets of experimental data were collected for the training of proposed machine learning technique. The geometric parameter and the training data Reynolds number are in tab. 1 [15].

Table 1. Data obtained for training

Type	N_b	S_b	N_t	D_c	Re_o
HX1	9	48	158	48	1148, 1413, 3121, 4365, 4979, 5669, 5843, 6702, 6996
HX2	7	70	176	0	296, 525, 697, 821, 1102, 1253, 1399, 1486, 1693, 1825
HX3	9	48	158	48	571, 745, 981, 1950, 2591, 2565, 3045, 3507, 4949, 5536, 7018

Table 2, then, gives the test data for the heat transfer rate prediction.

Table 2. Test data

Re_o								
378[a]	912[a]	1371[c]	1978[b]	2610[b]	3480[b]	4251[c]	5761[c]	6625[c]

Artificial neural network

The ANN is one of the well performing machine learning technique, it is used in various application. The ANN is modelled based on the imitation of human neural system. It can perform the most of the activities of human brain. The structure of ANN is made up of interconnected links with neurons, which helps to transfer the data from input to output. It is one of the most adaptive and flexible machine learning approach.

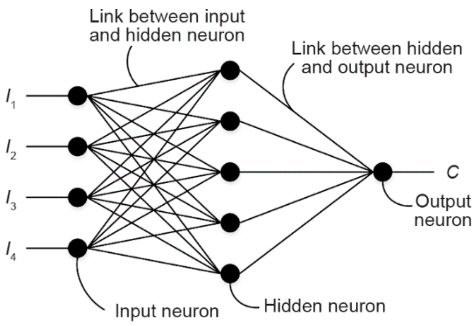

Figure 4. Structure of ANN

It has a major process as learning to adjust the weight to obtain the accurate output or prediction. It is widely used in pattern recognition, robotics, *etc.* The typical ANN consists of layers which are in three types, among one input and output layer as well as the structure has one or more hidden layers. In every layer number neurons are configured based on the input and output size. Then the ANN architecture is complex based on its hidden layer size. The structure of simple neural network is given in fig. 4.

The proposed system has four input, which are geometry of the exchanger and the output is heat transfer rate that is only one output. Hence four neurons are considered in the input side and one neuron in the output side. The mathematical function to calculate the output of the neural network is given:

$$C = \sum_{j=1}^{M} \frac{w_j^O}{1 + \exp\left(-\sum_{i=1}^{N} I_i w_{ij}^I\right)} \tag{2}$$

In eq. (2), I_i represents the i^{th} input value, w_i^o – the weights assigned between output and hidden layer, w_{ij}^I – the weight assigned between hidden and input, and M – the number of hidden neurons.

Then the learning error rate of ANN can be calculated:

$$\partial_k = \frac{1}{2}(Y - C)^2 \tag{3}$$

where ∂_k is the the k^{th} learning error, Y – the actual output value or class, and C – the ANN output or obtained class.

Teaching learning optimization

The TLO is a meta-heuristics search algorithm, which execute based on the population. In general the meta-heuristics algorithms are in two types, which are swarm and evolutionary algorithm. There are many algorithms under these two categories, these algorithms required controlling parameters such as population size, elite size, number of generation, *etc.* But in TLO not required most of these controlling parameters and it required only number of generation and population size.

The TLO algorithm is developed based on the imitation of teaching learning process of teachers. Its procedure is based on the teaching procedure of teacher's efforts to improve the student's quality. The process of TLO algorithm is divided in to two, they are teachers phase and learners phase.

Teachers phase: It is the initial phase of the TLO algorithm, in which the teachers trying to teach the student and measure their average rank or mark to evaluate their quality.

Learners phase: It is the second phase in which the learners themselves iterate to improve their performance. In which the learners interact with other learners to update the performance. The learners trying to learn new information from the other learners in the population.

Proposed TLONN

The TLONN is the combination of teaching learning optimization and neural network. In this hybrid algorithm the conventional neural network is adapted for the classification or the prediction of rate of heat transfer. The neural network includes two major part, such as training and testing. In the training stage the back propagation training algorithm was used to reduce the learning error, it has some issues. Hence in the proposed work we used the teaching learning algorithm for the effective training of ANN so that the proposed technique can effectively reduce the learning error rate. The step by step procedure of the proposed technique is given as follows.

Step 1. Initialization and data collection

In the first step the motivated problem should be formulated and the data required for the training of the ANN should be collected either by experimentation or for open source.

Step 2. The ANN modelling

In this step the ANN is modelled based on the proposed problem, in which the desired size of input, output and hidden neuron is assigned.

Step 3. The TLO for ANN learning

In this stage the TLO is executed to train the ANN. Here the total weight required for the ANN is assigned as the population and the teacher and learner phase is executed for more than 50 iteration. The optimal weights obtained after the TLO process is summarized as the final weight for the ANN.

Step 4. The ANN testing

In this stage the trained ANN is tested to evaluate the prediction accuracy of the network. In which a random geometry or input value is given to the ANN and compare the obtained output with the actual output.

Performance evaluation

Performance of the proposed TLONN is tested using the shell and tube exchanger data collected from [15]. Then the analysis is executed in MATLAB and its performance is

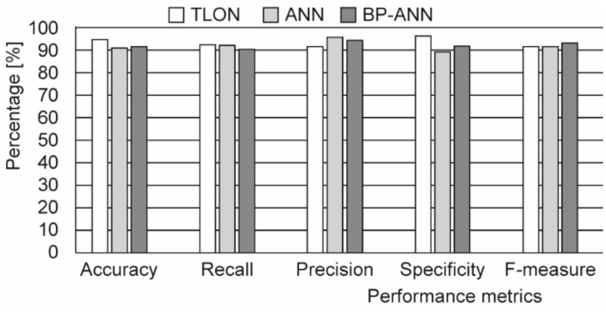

Figure 5. Performance comparison chart

compared with the conventional ANN with brake propagation (BP) training. The performance is compared based on the confusion matrix and precision, recall and accuracy. Figure 5 shows the performance comparison chart.

In fig. 5 the performance of various classifier for the prediction of heat transfer rate is given in which the various classifiers for the prediction of heat transfer rate is given. The chart clearly shows the variation of performance in different algorithm is clearly given. From the comparison it is evident that the proposed TLONN technique provided better accuracy than the other techniques.

Conclusion

In the proposed technique the shell and tube type heat exchanger is modelled as a classifier. The classifiers are used for the machine learning to ease most of the computational complexity. In this work we ANN as the machine learning technique to predict the heat transfer rate. In the proposed method the conventional ANN is modified using TLO, where the TLO is used for the training of ANN. In ANN the training is a major process, by using a better training method we can improve the prediction accuracy. Thus the learning error is reduced optimally by using TLO. Then the effectiveness of the proposed technique is proved by the performance analysis. Thus based on the analysis it is showed that the proposed technique is well adapted and suitable for the heat transfer rate prediction in heat exchanger.

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