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# Optimization of Heat Transfer Coefficient during Condensation of Refrigerant inside Plain Horizontal Tube using Teaching-Learning based Optimization Algorithm

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## Abstract

**Objectives**: To predict the optimum value of heat transfer coefficient during condensation of refrigerant inside a smooth horizontal tube using Teaching-Learning based Optimization Algorithm. **Methods**: Refrigerant vapor quality and mass flux are considered as variables. An objective function is formulated based on the Shah's correlation for heat transfer coefficient. The optimal results predicted by Teaching-Learning based Optimization Algorithm are validated with experimental data. **Results**: Refrigerant mass flux and vapor quality are varied from 100 to 500 kg/m2s and 0.1 to 0.9 respectively. The optimal value of heat transfer coefficient, refrigerant mass flux and vapor quality predicted by the algorithm are 7.56 kW/m2K, 493 kg/m2s and 0.87, respectively. **Conclusions**: The Teaching-Learning based Optimization Technique is capable of predicting the optimal set of values for different design and operating parameters.

**Keywords:** Condensation, Heat Transfer Coefficient, Refrigerant, Teaching-Learning based Optimization

## 1. Introduction

The condenser is an important heat exchanger widely used in refrigeration and air conditioning, process industries and power plants. The refrigerant and cooling water flow through two passes separated by a wall. The heat from the refrigerant to cooling water takes place by mainly convection. The heat transfer rate between refrigerant and water is governed by a convective heat transfer coefficient and heat transfer area. This heat transfer is accomplished at the rate of pump work. The heat transfer between refrigerant and water may be enhanced by either enhancing the heat transfer coefficient or heat transfer area. But due to the size and economic constraint the heat transfer area cannot be increased beyond a certain limit, so the aim of the researchers is to enhance convective heat transfer coefficient.

The heat transfer coefficient depends upon several parameters like, mass flux and vapor quality of refrigerant, inner diameter of tube, Reynolds's number, Prandtl number and properties of refrigerant. The parameters affecting the heat transfer coefficient are required to be optimized by either stochastic or deterministic nature of optimization techniques.

Several researchers have used different optimization techniques such as Particle Swarm Optimization (PSO), Artificial Neural Network (ANN), Genetic Algorithm (GA) and some other optimization techniques to opti-

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mize the design of heat exchangers. In[1] estimated the maximum heat transfer rate and minimum pressure drop in shell and tube heat exchangers using Genetic Algorithm. In[2] optimized thermal and economic aspects of shell and tube condenser by implementing genetic and Particle Swarm Optimization algorithms. In[3] used Teaching-Learning based Optimization method to optimize the thermal performance of a solar air heater. In[4] optimized the cost, weight, pressure drop and effectiveness of plate fin heat exchanger through multi objective Teaching-Learning based Optimization Algorithm. In[5] presented optimized value of cost and effectiveness of plate fin heat exchanger using modified Teaching-Learning based Optimization Algorithm. In[6] implemented Genetic Algorithm, Nelder-Mead method and nonlinear squares method to develop correlations for heat transfer coefficient, two phase friction factor frictional pressure drop and found these in good agreement with experimental results. In[7] used Artificial Neural Network method to predict the most affecting parameter on heat transfer and pressure drop during condensation of refrigerant during condensation of R-134a inside downward tube. In[8] utilized genetic and Particle Swarm Optimization algorithms for entropy minimization of fin type heat sink. In[9] optimized multi-stream plate fin heat exchanger based on the entropy generation minimization principal using Genetic Algorithm.

The objective of this work is to find the optimized set of design and operating parameters during condensation of refrigerant inside horizontal plain tube through the teaching - learning based optimization technique.

## 2. Teaching-Learning based Optimization Technique (TLBO)

Teaching-Learning based Optimization Technique is a teaching-learning process inspired algorithm proposed by[10]. Figure 1 denotes the flow chart of TLBO algorithm. In this optimization algorithm, a group of students reflects the population and subjects offered to them are taken as different design parameters. The Learners' output reflects the 'fitness' values of the objective function. The teacher is taken as the best solution among the entire population Crepinsek[11].

The working of Teaching-Learning based Optimization Algorithm has been divided into "Teacher phase" and "Learner phase". Let us consider two teachers 'A' and 'B' are teaching in two different classes C1 and C2. It is assumed that both teachers are teaching the same subject of the equal content to the equal merit level of students. Figure 2 depicts the marks distribution obtained by students of classes C1 and C2 evaluated by own teachers. The marks of students are taken normally distributed. In Figure 2, curves 1 and 2 represent the marks distribution of students taught by teachers A and B respectively. The normal distribution is calculated by the Equation 1.

$$f(x) = \frac{1}{\sigma\sqrt{2\Pi}} \exp\left\{\frac{-(x-\mu)^2}{2\sigma^2}\right\} \qquad (1)$$

Here, $\mu$, $\sigma^2$ and x are mean, variance and the value for which normal distribution is to be calculated. Figure 2 reveals that the mean value ($M_B$) of curve 2 is greater than curve 1 value ($M_A$). Every teacher will attempt to raise the mean of his/her class according to his/her ability. In the present case, the teacher 'A' will make an effort to bring mean $M_A$, near to his/her level and then towards mean $M_B$. As mean $M_A$ becomes equal to mean $M_B$, a new more learned teacher 'B' is required.

### 2.1 Teacher Phase

Let at any iteration i, $M_i$ is the mean of marks obtained by students and $T_i$ be the teacher. As $T_i$ makes an effort to bring mean $M_I$ near to his/her level, so $M_{new}$ is the modified mean of teacher $T_i$. The change between modified mean and old mean is evaluated as suggested by[10].

$\text{Difference\_Mean} = r_i (M_{new} - T_F M_i)$

Here $T_F$ is teaching factor taken as either 1 or 2 and $r_i$ any random number between 0 and 1. The current solution is updated as given below:

$X_{new, i} = X_{old, i} + \text{Difference\_Mean}_i$

### 2.2 Learner Phase

In this phase students enhance their knowledge by communicating randomly with other students. A student learns something new if the other student is more learned. The learner modification is made as suggested by[10–12].

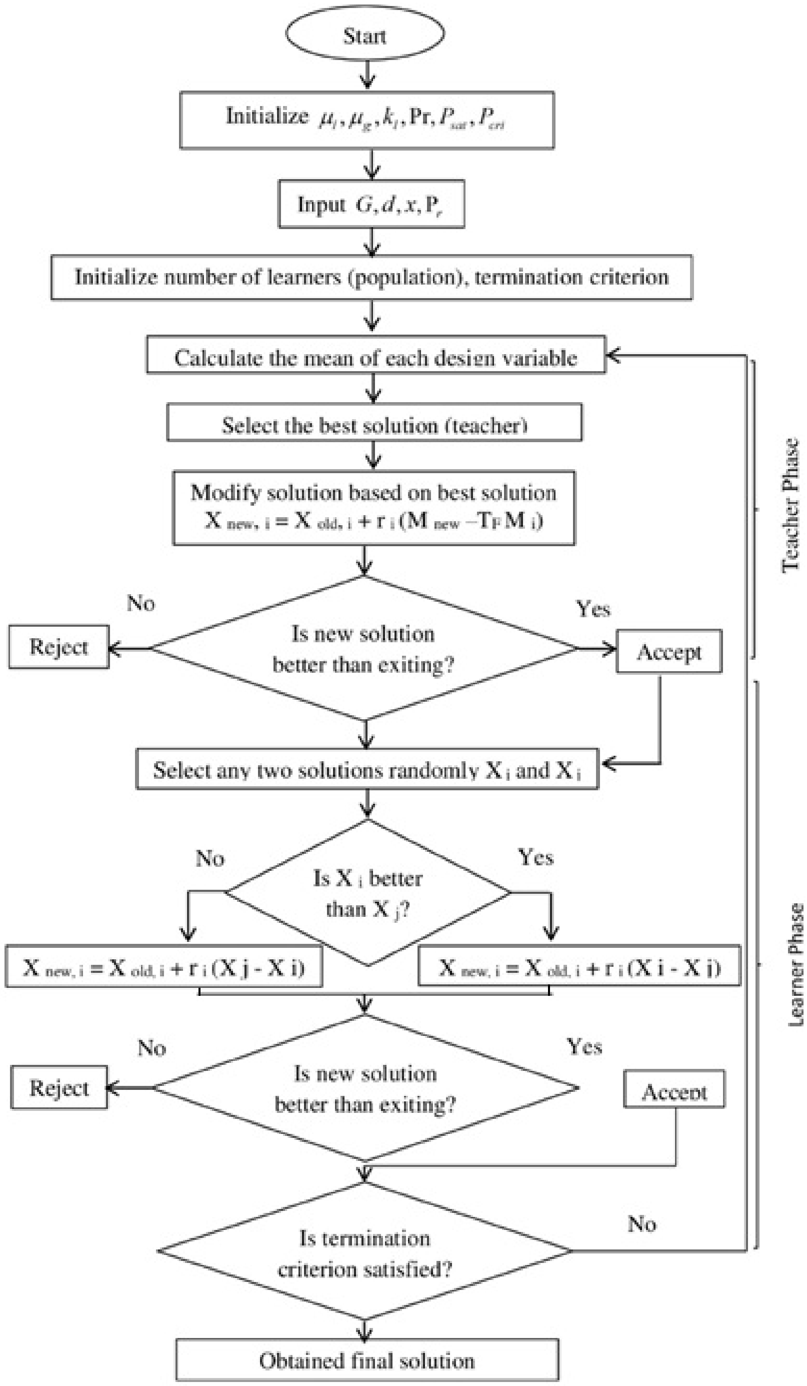


**Figure 1.** Flow chart of Teaching-Learning based Optimization Algorithm.

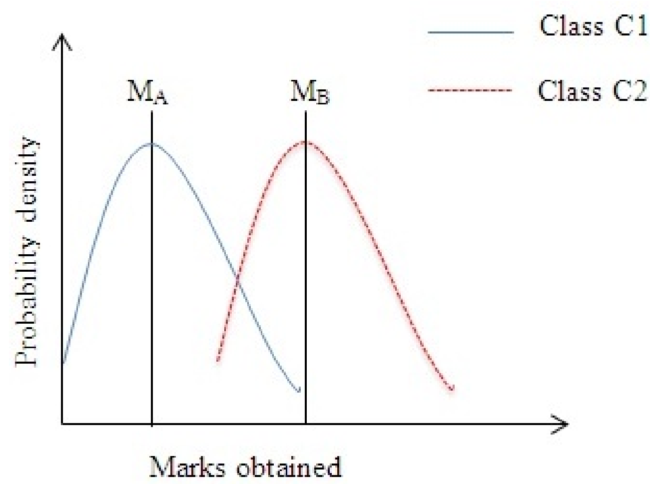


**Figure 2.** Marks distribution of students.

for i = 1:$P_n$
Arbitrarily another student $X_j$ selected such that $i \neq j$.
if $f(X_i) < f(X_j)$
$X_{new,i} = X_{old} + r_i (X_i - X_j)$
else
$X_{new,i} = X_{old} + r_i (X_j - X_i)$
end
$X_{new}$ is accepted if it yields an improved function value.

## 3. Experimental Set-Up

The Teaching-Leaning based Optimization Algorithm results are authenticated with the data collected from the experimental system shown in Figure 3. The experimental system consists of two test condensers. Each test condenser is a two concentric tube of length one meter. The inner tube is made of hard drawn copper having 9.4 mm and 12.76 mm inside and outside diameters respectively. The outer tube made of galvanized iron having

**Table 1.** Operating parameters

| **Parameters** | **Value** |
|---|---|
| Refrigerant mass flux (G) | 100 - 250 kg/m$^2$s |
| Heat flux (q) | 7.5 - 20.5 kW/m$^2$ |
| Condensing pressure (P) | 20 k Pa |
| Condensing temperature (T) | 35.95$^0$C |
| Vapor quality (x) | 0.1 - 0.9 |

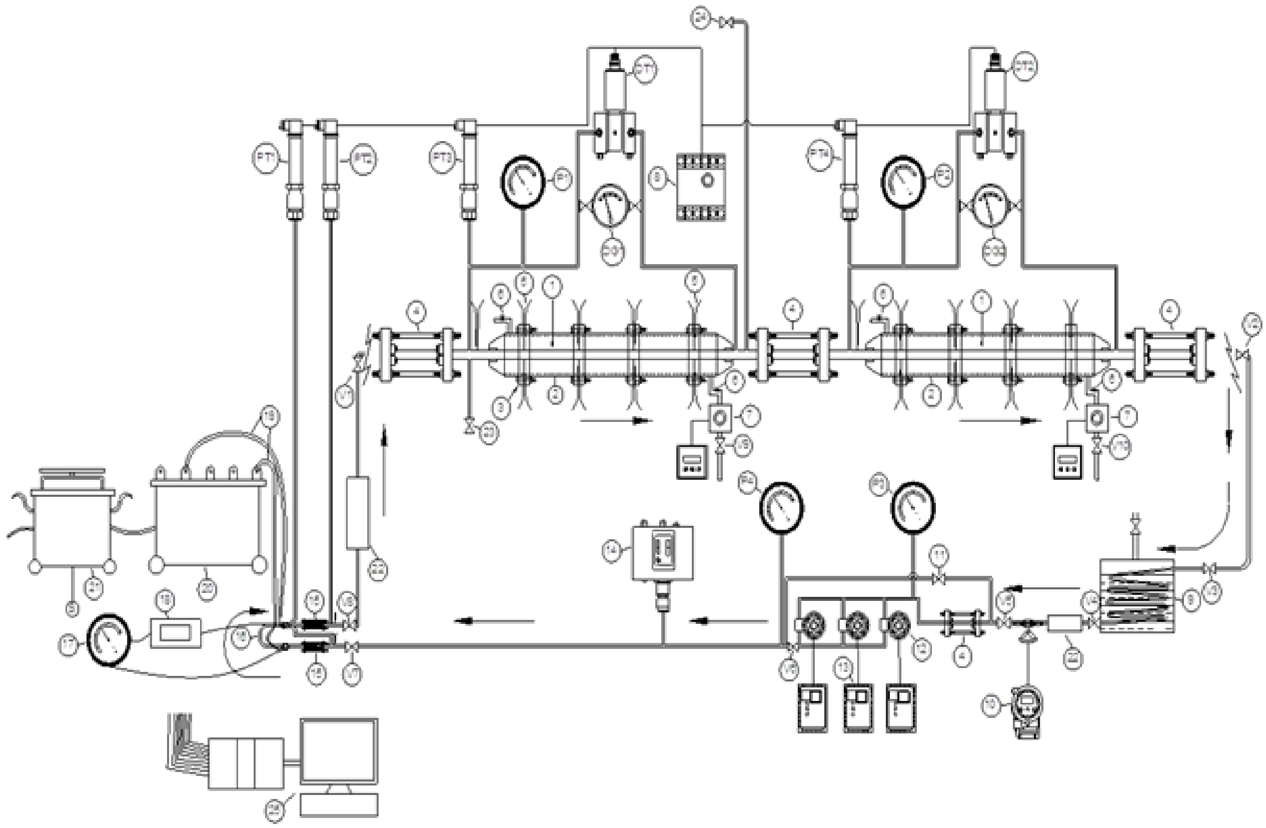

**Figure 8.**

1. Test-section
2. Outer tube
3. Flanged joint
4. Visual section
5. Thermocouple
6. Thermopile
7. Turbine flow- meter
8. 24 V DC power supply
9. Post-condenser
10.Coriolis mass flow meter
11. By-pass valve
12. Pump
13. Frequency controller
14. HP cut-out
15. Electrical isolator
16. Evaporator
17. Voltmeter
18. Power analyser P Pressure gauge
19. Cable DG differential pressure gauge
20. Transformer DT pressure -transducer
21. Variac
22. Filter
23. Charging valve
24. Purge valve
25. Data acquisition system

inner and outer diameters 43 mm and 50 mm respectively. The experimental data are collected based on the operating parameters shown in Table 1. The experimental data are recorded by a multichannel data acquisition system. Cooling water and refrigerant R-245fa vapor are circulated in the counter flow direction inside the each test section. Some mass of R-245fa vapor gets condensed in test sections. The refrigerant vapor then passed through post condenser where entire vapor condensed. This entirely condensed refrigerant passes through the evaporator. The evaporator is a stainless steel tube having 16 mm inside diameter, 1.5 mm thickness and 3.6 m length. The quality of vapor produced in evaporator was controlled by a step-down transformer. The refrigerant is circulated through a bank of three gears connected in series. The refrigerant mass flow rate is controlled using a corioles mass flow meter. To get the fair temperature of inner tube four T-type thermocouples are installed at four axial locations of each test section. The refrigerant pressure at the entry and exit of test section was measured by pressure gauge. The pressure difference across the test condenser was measured using a differential pressure transducer.

## 4. Problem Formulation

Several empirical correlations have been developed to determine two-phase condensation heat transfer coefficient during condensation of refrigerants flowing through a smooth horizontal tube. In[13,14] correlations better predicts the heat transfer coefficient during the condensation of R-245fa flowing through a plain horizontal tube.

The objective function formulated for the optimization of R-245fa condensation heat transfer coefficient is based on Shah Correlation which is calculated by using Equations 2-6.

$$\text{Maximize } h = 0.023\times \mathrm{Re}^{0.8}\times \mathrm{Pr}^{0.4}\left(\frac{\mu_l}{14\mu_g}\right)^n \times\left[(1-x)^{0.8}+\frac{3.8\times x^{0.76}\times(1-x)^{0.04}}{P_r^{0.38}}\right]\times\left(\frac{k_l}{d}\right) \quad (2)$$

Here,

$$n = 0.0058 + 0.557\,\mathrm{P}_r \quad (3)$$

$$\mathrm{Re} = \left(\frac{G\times d}{\mu_l}\right) \quad (4)$$

$$\mathrm{Pr} = \frac{\mu_l\times C_p}{k_l} \quad (5)$$

$$P_r = \frac{P_{sat}}{P_{cri}} \quad (6)$$

## 5. Results and Discussion

### 5.1 Variation in Heat Transfer Coefficient with Refrigerant Mass Flux and Vapor Quality

The Figure 4 represents the influence of refrigerant mass flux and vapor quality on the heat transfer coefficient during condensation of R-25fa inside plain horizontal tube. As could be inferred from the figure, the heat transfer

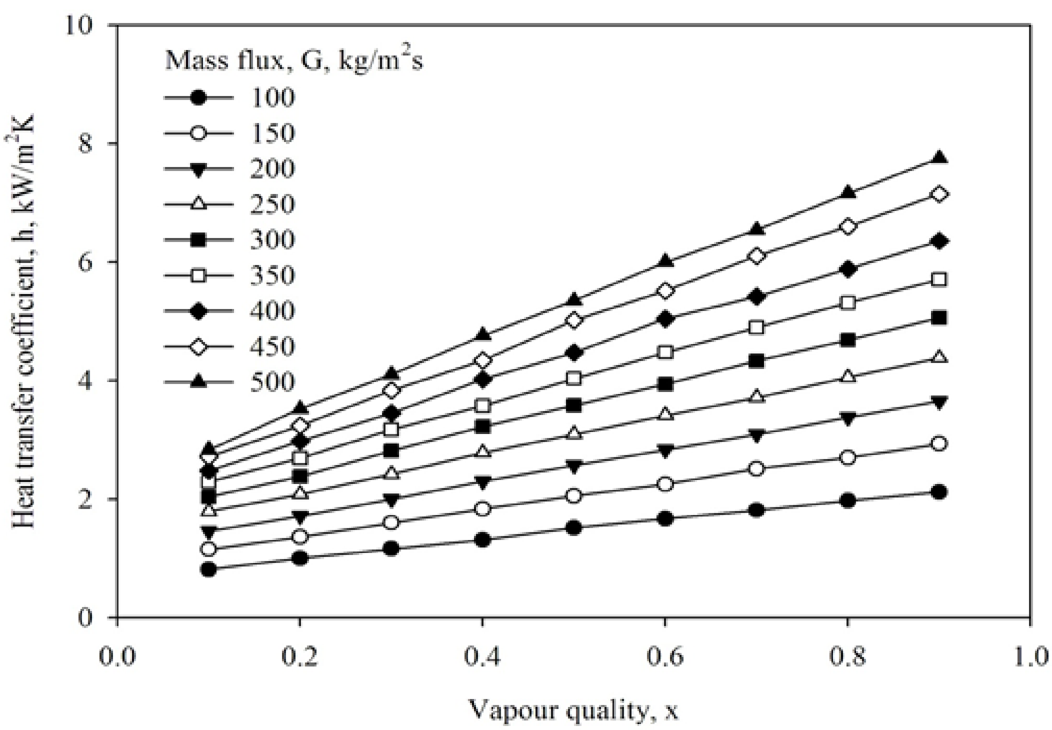


**Figure 4.** Variation in heat transfer coefficient with vapor quality.

coefficient increases with increase in refrigerant mass flux and vapor quality. The increase in refrigerant mass flux creates more turbulence in the flow inside the tube, resulting in better mixing of refrigerant vapor, producing high heat transfer coefficient. At high refrigerant vapor quality there is a thinner liquid film on the inner wall of the tube offering low thermal resistance leads to the high value of heat transfer coefficient while at low vapor quality the condensate accumulated at the lower part of the tube leads low heat transfer coefficient as reported by[15,16].

## 5.2 Teaching-Learning based Optimization Results

The Teaching-Learning based Optimization Algorithm is run, Equation 2 as the optimization function to optimize the heat transfer coefficient during condensation of R-245fa inside horizontal tube. The variables with their bounds are listed in Table 2. The TLBO algorithm is run using the following parameters.

Number of runs = 50
Number of population = 10
Number of iterations = 10
Teaching factor ($T_F$) = 2

At first the optimization algorithm is run at constant refrigerant mass flux while vapor quality varies as according to Table 2. The refrigerant mass flux value is started from 100 kg/m$^2$s and increased by 50 kg/m$^2$s up to 500 kg/m$^2$s. The consistency of results predicted by the

**Table 2.** Variables and their bounds

| Variables | Bounds |
|---|---|
| Mass flux of refrigerant (kg/m$^2$s) | 100 - 500 |
| Vapor quality | 0.1 – 0.9 |

**Table 3.** Comparison between TLBO predicted and experimental

| Mass flux (kg/m$^2$s) | Vapour quality | | Heat transfer coefficient (kW/m$^2$K) | |
|---|---|---|---|---|
| | Experimental | TLBO | Experimental | TLBO |
| 100 | 0.9 | 0.88 | 1.96 | 2.13 |
| 150 | 0.9 | 0.89 | 2.35 | 2.72 |
| 200 | 0.9 | 0.88 | 2.88 | 3.26 |
| 250 | 0.9 | 0.89 | 3.51 | 3.91 |
| 300 | 0.9 | 0.87 | 4.16 | 4.59 |
| 350 | 0.9 | 0.89 | 4.98 | 5.15 |
| 400 | 0.9 | 0.895 | 5.84 | 6.17 |
| 450 | 0.9 | 0.893 | 6.24 | 6.86 |
| 500 | 0.9 | 0.88 | 6.92 | 7.65 |

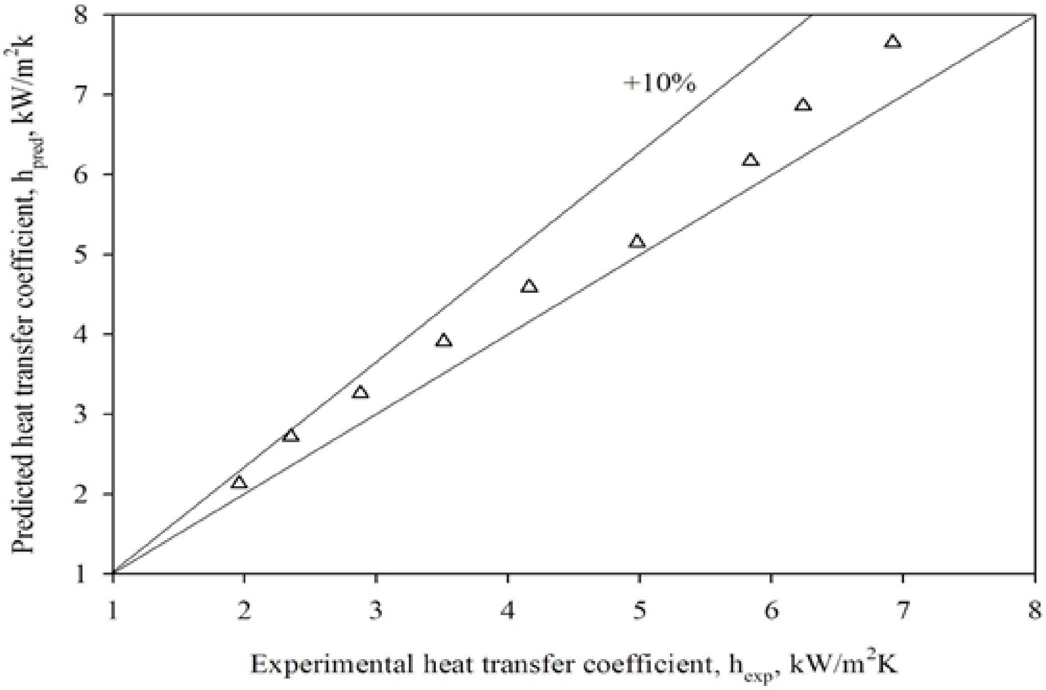


**Figure 5.** TLBO predicted heat transfer coefficient versus experimental heat transfer coefficient.

algorithm is checked by running the algorithm 25 times at each condition and the average result is calculated for every mass flux. This average calculated value is the optimized value of the heat transfer coefficient at every mass flux. The optimum value of heat transfer coefficient and vapor quality predicted by TLBO algorithm is compared with the experimental results. Table 3 displays the comparison in TLBO and experimental results. As could be witnessed from the table the maximum heat transfer coefficient predicted at vapor quality almost equal to 0.9 which is similar to experimental. To know the deviation between the TLBO predicted and the experimental heat transfer coefficient a graph is plotted against the experimental results as shown in Figure 5. As could be observed

**Table 4.** Comparison of optimized results

| Parameters | Experimental | TLBO |
|---|---|---|
| Mass flow rate of refrigerant (kg/m$^2$s) | 500 | 493 |
| Vapor quality | 0.9 | 0.87 |
| Optimum value of heat transfer coefficient (kW/m$^2$K) | 6.92 | 7.56 |

from this figure all predicted results fall within an error band of +10%.

The TLBO algorithm is run again to optimize the heat transfer coefficient for variable refrigerant mass flux and vapor quality. The refrigerant mass flux and vapor quality vary as according to Table 2. The set of optimized values predicted by TLBO algorithm is compared with the experimental values. Table 4 depicts the comparison between TLBO and experimental. The value of maximum heat transfer coefficient 7.56 kW/m$^2$K is reported at refrigerant mass flux 493 kg/m$^2$s and vapor quality 0.87. These values of heat transfer coefficient, refrigerant mass flux and vapor quality are also almost equal to experimental.

## 6. Conclusions

In the present work condensation heat transfer is optimized. Teaching-Learning based Optimization Algorithm is employed for the optimization of heat transfer coefficient during condensation of R-245fa inside plain tube. The value of maximum heat transfer predicted by the algorithm is 7.56 kW/m$^2$K for refrigerant mass flux 493 kg/m$^2$s and vapor quality 0.87. The TLBO results are compared with experimental and found in good agreement with each other. It may be inferred that the TLBO is capable of predicting the optimized heat transfer coefficient during condensation of refrigerant. This makes TLBO an effective optimization technique to optimize the design and operating parameters to optimize the condensation heat transfer.

## 7. Nomenclature

$C_p$ Specific heat (kJ / kg K).

D Outer tube diameter of inner tube (mm).

d Inner tube diameter of inner tube (mm).

G Mass flux (kg/m$^2$.s).

h Heat transfer coefficient (kW/m$^2$ K).

k Thermal conductivity (W/m K).

x Vapor quality.

μ Viscosity (μPas).

Re Reynolds number.

$P_r$ Reduced pressure.

Pr Prandtl number.

l liquid.

g gas.

L left.

T top.

B bottom.

R right.

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