Enhancement of Effectiveness of Heat Exchangers Using Nano Fluids And Its Prediction Using Machine Learning

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Abstract: Heat exchangers are crucial for efficient heat transfer in industries, enabling energy recovery and process optimization. Meanwhile, nanofluids enhance thermal properties with high conductivity nanoparticles, finding diverse applications in heat exchangers. Together, they ensure optimal thermal management, improving system efficiency and industrial sustainability.

Using machine learning for predicting mechanical system behavior has emerged as a powerful tool in engineering applications. By analyzing historical data on system parameters, operating conditions, and performance metrics, machine learning models can forecast future behavior, such as overall system performance. The integration of machine learning into mechanical systems promises to revolutionize to enhance operational efficiency in various industries.

This project explores an innovative approach to Enhance heat transfer processes by incorporating nanofluids, which are fluids infused with nanoscale particles. Leveraging the power of machine learning, aims to predict the enhancement of heat exchanger efficiency. Traditional methods of heat transfer often face limitations, and our study seeks to address these challenges through the integration of advanced materials.
The experimental investigation is carried out on a shell and tube heat exchanger using nanofluid at concentrations of 2%, 4%, & 6% with base fluid in parallel and counterflow conditions and determined its effectiveness and overall heat transfer coefficient.

In this work, machine learning is employed to analyze and predict the effectiveness and heat transfer coefficient of heat exchanger using nanofluids under various conditions. Algorithms such as Decision tree and Random forestry are employed and found that Decision tree is predicting accurate values which are same as experimental values than Random forestry algorithm.

Keywords: HEAT EXCHANGER, NANOFLUIDS, DECISION TREE ALGORITHM, RANDOM FOREST ALGORITHM etc.

1.INTRODUCTION

- Heat Exchangers: Heat exchangers facilitate thermal energy transfer between fluids or gases without direct contact, crucial in diverse industries. They employ a solid barrier to ensure separation while enabling efficient heat exchange through conduction, widely utilized for fluid and gas heating or cooling.

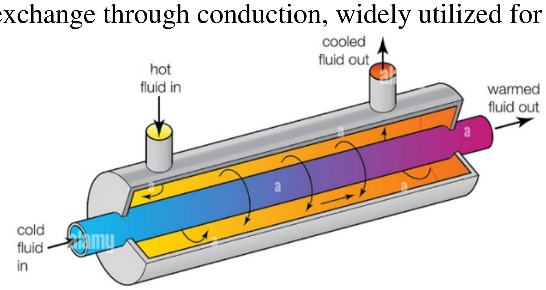

Fig1: Shell and Tube Heat exchanger

- WORKING FLUIDS USED IN HEAT EXCHANGERS: Heat exchangers can utilize various fluids depending on the specific application and requirements. The choice of working fluid depends on factors such as temperature range, pressure, heat transfer efficiency, environmental considerations, and cost. Here are some common types of working fluids used in heat exchangers: Water, Refrigerants, Oil, Steam, Air, Glycol Solutions, Molten Salts, Heat Specialized Fluids
- NANO FLUIDS: Nanofluids, engineered fluids with nanoparticles dispersed in a base fluid like water or oil, enhance thermal conductivity and convective heat transfer. Incorporating metals or oxides in nanometer sizes alters properties, making them ideal for heat exchangers and cooling systems, promising efficiency boosts in thermal applications.

- MACHINE LEARNING: Machine learning, a branch of artificial intelligence, enables computers to learn from data and make predictions without explicit programming. By learning patterns from data, it facilitates prediction in diverse fields, leveraging acquired knowledge for decision-making on unseen data.

II. EXPERIMENTAL INVESTIGATION

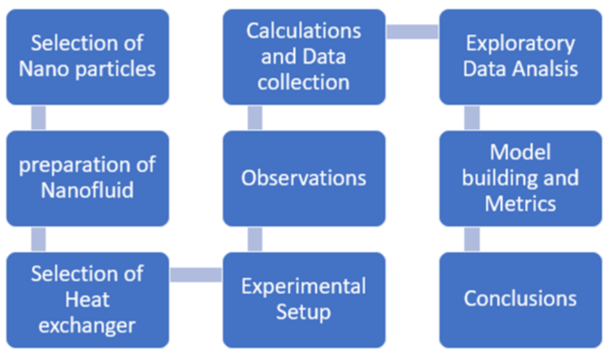

Fig 2: Research methodology flowcharts

A.Selection of Nanoparticle Materials:

Fig 3: Aluminum oxide nanoparticle

The choice of nanoparticle materials is pivotal in determining the performance and stability of nanofluids utilized in heat exchanger applications. In this section, we delineate the rationale behind selecting aluminum oxide nanoparticles for augmenting the heat transfer effectiveness of the shell and tube heat exchanger. Thermal Conductivity Enhancement, Stability and Compatibility, Cost-effectiveness & Particle Size and Shape.

B. Preparation of Nano Fluids:

Preparation of Nano Powder:

Aluminum oxide is a mixture of aluminum and oxygen, it is known as alumina. Al2O3 Nano powder. A mixture of alumina particles is generally obtained by sol-gel method.

Aluminum chloride hexahydrate is dissolved in distilled water in a beaker, followed by drop-wise addition of ammonium hydroxide to maintain pH at 7. Triton X100 serves as a surfactant. The resulting white gel precipitate is washed multiple times with hot distilled water using ultrasonic cleaning, then dried in a hot air oven at 100°C for 15 hours. Grinding the dried content yields alumina powder, further processed to obtain alumina Nano powder through calcination.

Preparation of Nanofluid:

A two-step procedure is used to prepare alumina nano fluid. The formula for calculating concentration is Concentration (%) = (X/Y) x100, where X is the solute's (alumina nano fluid) volume and Y is the solution's (water) volume..

C. Selection of Heat Exchanger:

According to a literature review, Shell tube heat exchanger is considered for experimental investigation because of its suitability with nanofluids as the working fluid, based on its demonstrated efficacy and compatibility in prior studies.

D. Experimental Setup:

Experimental setup consists of shell and tube heat exchanger with Geyser. Geyser is employed to supply hot working fluid in the shell of heat exchanger whereas Cold fluid flows in its tube.

Fig 4: Experimental setup

Modifications:

1. A pump is employed to pump the working fluid from reservoir to the inlet of the tube.
2. Removed the Three-way water pipe made a direct water inlet to geyser

E. Experimental Procedure:

1. Switch on the M.C.B, Mains on.
2. Start the flow of water to Geyser and switch on the geyser so that hot water starts flowing through the pipe.
3. Now the flow of cold water has started.
4. Using the valves provided the flow can be adjusted to counter / parallel.
5. Until the steady state is attained, maintain the same flow rate.
6. Note down the Temperatures T1, T2, T3 & T4.
7. For counter or parallel flow with a constant flow rate, repeat the experiment.
8. Repeat the above 1 to 7 steps for Nano fluid with different concentrations of 2%, 4% and 6% with base fluid

F. Model Calculations:

Formulas:

1. $Q_h= m_hC_{ph}(T_{hi} – T_{ho})$ in watts.

Where, m_h = mass flow rate of hot water in LPs.

C_{ph} = Specific heat of water = 4187 J/kg °K

T_{hi} = Inlet temperature of hot water

T_{ho} = Outlet temperature of hot water

2. $Q_c= m_hC_{pc} (T_{co}- T_{ci})$ in watts.

Where, mc = mass flow rate of cold water in LPs.

C_{pc} = Specific heat of water = 4187 J/kg °K

T_{ci} = Inlet temperature of cold water

T_{co} = Outlet temperature of cold water

3. $Q = (Q_h + Q_c) / 2$ in watts

4. LMTD = $(\theta_2 - \theta_1) / \text{Ln} (\theta_2/ \theta_1)$ °K

For Parallel flow,

Where, $\theta_1 = (T_{hi} – T_{ci})$ & $\theta_2 = (T_{ho} – T_{co})$

For Counter flow,

Where, $\theta_1 = (T_{ho} – T_{ci})$ & $\theta_2 = (T_{hi} – T_{co})$

5. U_o (overall heat transfer coefficient): Q/ (A x LMTD)

Where, A= π d L in m^2 = 3.14 x 0.025 x 1.1= 0.0863 m^2

Effectiveness:

if, $m_cC_{pc} > m_hC_{ph}$ = h = $T_{hi} – T_{ho} / T_{hi} - T_{ci}$

if, $m_cC_{pc} < m_hC_{ph}$ = h = $T_{co} – T_{ci} / T_{hi} - T_{ci}$

Thi = 35°c, Tho = 33.5°c, M-h = 0.016

Tci = 33.6°c, Tco= 34.6°c, M-c = 0.012

1. Q_h = 0.016 x 4187 x (35 – 33.5) = 100.48 in watts

2. Q_c= 0.012 x 4187 x (34.6 - 33.6) = 50.24 in watts

3.Q = (100.48 + 50.24) / 2= 75.36 in watts

4. LMTD = (1.1 - 1.4) / Ln (1.1/1.4) = 1.24 °K

5. U_o= 75.36 / 0.0863 x 1.24 = 702.02 (w / m^2 °k)

6. X = (34.6 - 33.6) / (35 – 33.6) = 0.71

The above model calculation procedure is done for all concentrations of nanofluids with parallel and counter flow conditions

- Water + 2% of Nano fluid as working fluid in parallel flow

T1 (Hi)	T2 (Ho)	T3 (Ci)	T4 (Co)	M-h (sec)	M-c (sec)	Uo (W/m2k)	X
34	32	30	31.1	0.017	0.013	557.20	0.28
35.6	32	30.1	31.3	0.017	0.013	788.24	0.22
37.2	32.1	30.18	31.4	0.017	0.013	892.61	0.17
38.9	32.2	30.25	31.5	0.017	0.013	981.03	0.14
40.6	32.3	30.3	31.7	0.017	0.013	1112.39	0.14
42.7	32.54	30.36	31.9	0.017	0.013	1161.01	0.12
44.3	32.67	30.41	32	0.017	0.013	1192.36	0.11
46.02	32.82	30.45	32.5	0.017	0.013	1523.27	0.13
47.65	32.9	30.46	32.9	0.017	0.013	2026.70	0.14
49.25	33	30.48	33.3	0.017	0.013	1669.72	0.15
50.95	33.7	30.5	33.65	0.017	0.013	2347.93	0.15
52.65	34.5	30.52	34	0.017	0.013	1477.69	0.16
54.25	34.9	30.58	34.35	0.017	0.013	1466.07	0.16
56.6	35.7	30.6	34.7	0.017	0.013	1269.42	0.16
57.55	36.4	30.65	35.2	0.017	0.013	1208.23	0.17
59.25	37.2	30.67	35.8	0.017	0.013	1168.90	0.18
60.95	38	30.7	36.45	0.017	0.013	1148.56	0.19
64.7	38.7	30.72	36.9	0.017	0.013	1137.76	0.18
65.3	40.6	30.77	37.4	0.017	0.013	917.24	0.19
67.1	42.4	30.8	37.8	0.017	0.013	794.98	0.19

Table 1: Calculation of Water + 2% of Nano fluid as working fluid in parallel flow

- Water + 2% of Nano fluid as working fluid in Counter flow

T1 (Hi)	T2 (Ho)	T3 (Co)	T4 (Ci)	M-h (sec)	M-c (sec)	Uo (W/m2k)	X
34.7	32.8	33.2	33	0.017	0.013	318.94	0.12
36.18	32.9	33.43	33	0.017	0.013	1952.58	0.14
37.7	33.1	33.73	33.1	0.017	0.013	2095.29	0.14
39.18	33.2	33.9	33.1	0.017	0.013	2185.6	0.13
40.66	33.3	34.25	33.1	0.017	0.013	2006.21	0.15
42.1	33.3	34.65	33.2	0.017	0.013	2541.06	0.16
43.72	33.6	35	33.2	0.017	0.013	1869.41	0.17

45.42	34	35.3	33.3	0.017	0.013	1610.61	0.17
47.2	34.3	35.47	33.3	0.017	0.013	1462.3	0.16
48.6	34.6	35.62	33.4	0.017	0.013	1384.7	0.15
50.5	34.8	35.8	33.4	0.017	0.013	1350.53	0.14
52.5	35.4	36.5	33.5	0.017	0.013	1285.61	0.16
54.4	36.1	37.2	33.5	0.017	0.013	1208.94	0.18
56.2	36.6	37.8	33.6	0.017	0.013	1191.96	0.19
58.2	37.4	38.4	33.7	0.017	0.013	1131.23	0.19
60.1	38.3	38.8	33.7	0.017	0.013	1052.16	0.19
62.6	39.2	39.3	33.8	0.017	0.013	1006.16	0.19
64.9	40.2	39.7	33.8	0.017	0.013	951.26	0.19
66.1	41.1	40.1	33.9	0.017	0.013	909.59	0.19
67.3	41.9	40.6	33.9	0.017	0.013	884.61	0.2

Table 2: Calculation of Water + 2% of Nano fluid as working fluid in counter flow

III. MACHINE LEARNING

A. The Process Followed in Machine Learning:

STEP 1: Data collection

Data collection involves conducting experiments on a shell and tube heat exchanger to gather essential parameters. These include T1 (T_{hi}) for hot water inlet temperature, T2 (T_{ho}) for hot water outlet temperature, T3 (T_{co}) for cold water outlet temperature, T4 (T_{ci}) for cold water inlet temperature, U_o for the overall heat transfer coefficient, and X for effectiveness.

S.no	T1(T_{hi})	T2(T_{ho})	T3(T_{co})	T4(T_{ci})	U_o (W/m2k)	X
1	34.7	32.8	33.2	33	318.94	0.12
2	36.18	32.9	33.43	33	1952.58	0.14
3	37.7	33.1	33.73	33.1	2095.29	0.14
4	39.18	33.2	33.9	33.1	2185.60	0.13
5	40.66	33.3	34.25	33.1	2006.21	0.15
6	42.1	33.3	34.65	33.2	2541.06	0.16
7	43.72	33.6	35	33.2	1869.41	0.17
8	45.42	34	35.3	33.3	1610.61	0.17
9	47.2	34.3	35.47	33.3	1462.30	0.16

10	48.6	34.6	35.62	33.4	1384.70	0.15
11	50.5	34.8	35.8	33.4	1350.53	0.14
12	52.5	35.4	36.5	33.5	1285.61	0.16
13	54.4	36.1	37.2	33.5	1208.94	0.18
14	56.2	36.6	37.8	33.6	1191.96	0.19
15	58.2	37.4	38.4	33.7	1131.23	0.19
16	60.1	38.3	38.8	33.7	1052.16	0.19
17	62.6	39.2	39.3	33.8	1006.16	0.19
18	64.9	40.2	39.7	33.8	951.26	0.19
19	66.1	41.1	40.1	33.9	909.59	0.19
20	67.3	41.9	40.6	33.9	884.61	0.20

Table 3: Input and output parameters of the Experiment

In this initially function is called Before going to the Prediction:

```
[ ] import pandas as pd
    import matplotlib.pyplot as plt
    import seaborn as sns
    import numpy as np
    import warnings
    warnings.filterwarnings('ignore')
    %matplotlib inline

    df = pd.read_excel("/content/vasmshi cf 2 percent.xlsx")
    df.head()
```

	T1 (Hi)	T2 (Ho)	T3 (Co)	T4 (Ci)	Uo (W/m2k)	X (%)
0	34.70	32.8	33.20	33.0	318.94	0.12
1	36.18	32.9	33.43	33.0	1952.58	0.14
2	37.70	33.1	33.73	33.1	2095.29	0.14
3	39.18	33.2	33.90	33.1	2185.60	0.13
4	40.66	33.3	34.25	33.1	2006.21	0.15

Fig 5: ML data

STEP 2: Data Preprocessing

- Using Google Collaboratory, upload Data of Parameters in Colab.

STEP 3: Data Analysis in Machine Learning

- From Fig it is observed that the T3 and T1 values effecting the effectiveness (X) and overall heat transfer coefficient (U_o)

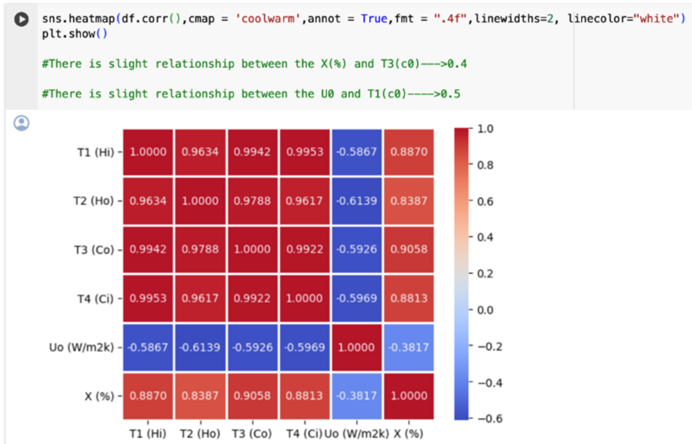

Fig 6: ML data

STEP4: Model Building

- The Test and Train data must be assigned independently
- Out of the entire dataset 100% that is supplied, only 20% test is offered,

Visualization:

- In this Using Matplotlib we can plot the Relationship between Input and output data used Input data as:

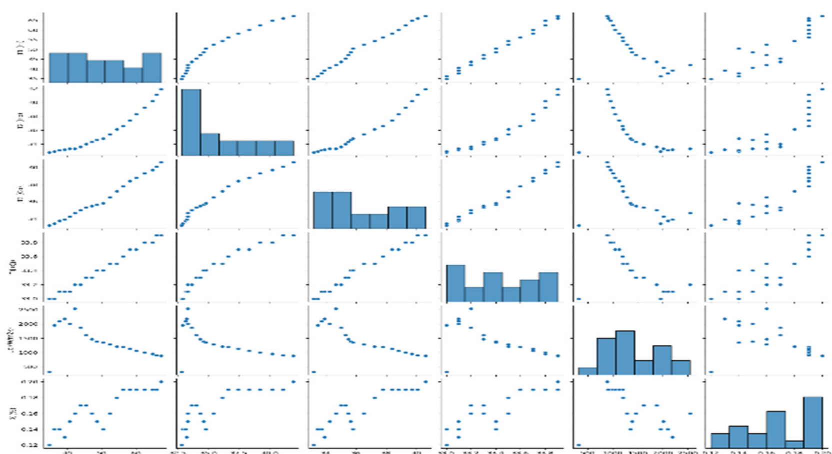

Fig 7: Paring plot visualization

STEP 5: MODEL EVALUATION

Model evaluation is a process of evaluating the considered algorithm which consists of how much error, Using Mean squared Error and Mean Absolute error

Decision Tree Regression:

Decision Tree is a Supervised learning technique that can be used for both classification and Regression problems, but mostly it is preferred for solving Classification problems

Mean Absolute Error (MAE): 0.00500 and Mean Squared Error (MSE): 0.000100

```
[26] from sklearn.model_selection import train_test_split
     X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

[27] from sklearn.tree import DecisionTreeRegressor
     # Initialize the Decision Tree Regressor model
     dt_regressor = DecisionTreeRegressor(random_state = 0)

[28] # Train the model on the training data
     dt_regressor.fit(X_train, y_train)

     DecisionTreeRegressor
     DecisionTreeRegressor(random_state=0)

[29] # Make predictions
     y_pred_dt = dt_regressor.predict(X_test)
```


```
[29] # Make predictions
     y_pred_dt = dt_regressor.predict(X_test)
```


```
[30] from sklearn.metrics import mean_absolute_error, mean_squared_error
     # Calculate mean absolute error (MAE)
     mae = mean_absolute_error(y_test, y_pred_dt)
     print(f"Mean Absolute Error (MAE): {mae}")

     # Calculate mean squared error (MSE)
     mse = mean_squared_error(y_test, y_pred_dt)
     print(f"Mean Squared Error (MSE): {mse}")

     Mean Absolute Error (MAE): 0.0050000000000000044
     Mean Squared Error (MSE): 0.00010000000000000018
```

Fig 8: Decision Tree Regression Algorithm

Random Forest Algorithm:

The Random Forest Algorithm in machine learning in a concise manner, Random Forest is a popular supervised learning algorithm that combines multiple decision trees to solve both classification and regression problems.

```
from sklearn.ensemble import RandomForestRegressor
random_forest = RandomForestRegressor(random_state=0)
random_forest.fit(X_train, y_train)

RandomForestRegressor
RandomForestRegressor(random_state=0)

[32] y_pred_rf = random_forest.predict(X_test)

pd.DataFrame(y_pred_rf)
```

	0
0	0.1401
1	0.1905
2	0.1897
3	0.1401

```
[34] from sklearn.metrics import mean_absolute_error, mean_squared_error
     mae_rf = mean_absolute_error(y_test, y_pred_rf)
     mse_rf = mean_squared_error(y_test, y_pred_rf)
     print("Mean Absolute Error (Random Forest):", mae_rf)
     print("Mean Squared Error (Random Forest):", mse_rf)

     Mean Absolute Error (Random Forest): 0.005250000000000102
     Mean Squared Error (Random Forest): 0.00010109000000000204
```

Fig 9: Random Forest Algorithm

From the algorithm, we can observe that the errors

Mean Absolute Error (Random Forest): 0.00525

Mean Squared Error (Random Forest): 0.000101

STEP 6: DEPLOYMENT:

- In this case, the Effectiveness value can be determined by running the cell in Colab.
- In this case the values is assigned for the new dataset.
- For each input's given case the data will be allocated into a separate row (predicted_value[0]) that row will be used for the prediction.

```
[ ] input_data= [[50,35,35,33]]
    dt_pred = dt_regressor.predict(input_data)
    rf_ped = random_forest.predict(input_data)

[ ] dt_pred

    array([0.17])

[ ] rf_ped

    array([0.1506])

[ ] input_data = [[50,35,35,33]]
    dt_pred = dt_regressor.predict(input_data)

[ ] rf_pred = random_forest.predict(input_data)

[ ] print(dt_pred)
    print(rf_pred)

    [1384.7]
    [1731.6939]
```

Fig 10: ML output Prediction Result

Mean Absolute Error:

```
df_metrics.sort_values(by=["metrics"],ascending=True).plot.barh()
plt.show()
```

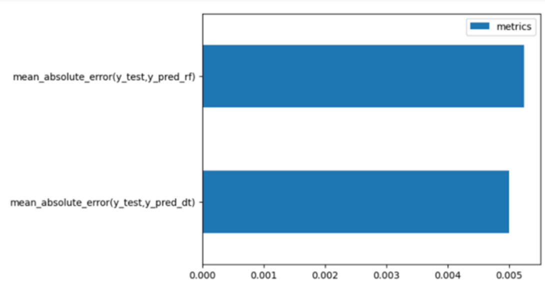

Fig 11: Metric Representation of MAE

Mean Squared Error:

```
df_metrics.sort_values(by=["metrics"],ascending=True).plot.barh()
plt.show()
```

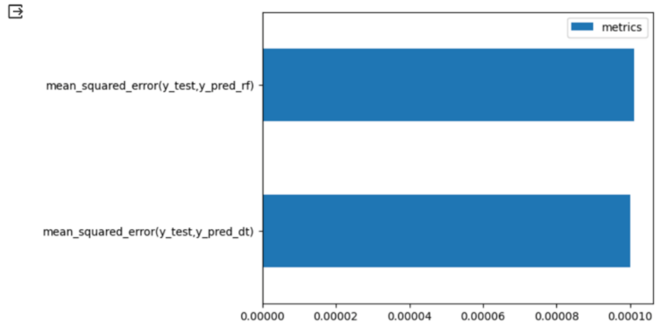

Fig 12: Metric Representation of MSE

IV. RESULTS

Temperature data from the experimental system were obtained for the shell and tube heat exchanger's inlet and exit. Prior to calculating the distinct volume concentration of Al_20_3/water Nano fluid at the same mass flow rate and input temperatures of both cold and hot situations, the heat transfer flow characteristics of Al_20_3 were first estimated. In this study, modest volume concentrations of nanofluids 2%, 4%, and 6%, respectively are employed experimentally. Utilizing them on a heat exchanger, they compute the overall heat transfer and Effectiveness under parallel and counterflow situations while maintaining the same intake temperature.

%	Parallel flow		Counter Flow	
	U_o(W/m^2 °K)	X	U_o(W/m^2 °K)	X
water	702.02	0.71	318.94	0.42
2%	557.20	0.28	884.61	0.20
4%	655.45	0.97	318.94	0.70
6%	1052.49	0.61	879.51	0.20

Table 4: Experimental results for base fluids and Nano fluids

First, the hot and cold fluid conditions for Al_20_3 were computed in this work. Determined the overall heat transfer coefficient and effectiveness after measuring the temperatures at the inlet and outflow where hot fluid is obtained from the shell side and nano fluids from the tube side. To calculate the overall heat transfer coefficient and effectiveness under both parallel and counterflow situations, temperature measurements are acquired during the experiment. The rate of heat transmission rises automatically as the volume concentrations rise.

When comparing flow conditions, overall heat transfer coefficient and effectiveness under parallel flow is greater than that under counter flow. It is observed that 1052.49 W/m^2 K is the highest overall heat transfer coefficient that can be estimated with a volume concentration of 0.6% and Effectiveness with the highest computed value is 0.97 at a volume concentration of 4% The total overall heat transfer coefficient and effectiveness has increased by more tha1.5 times in these final figures (13).

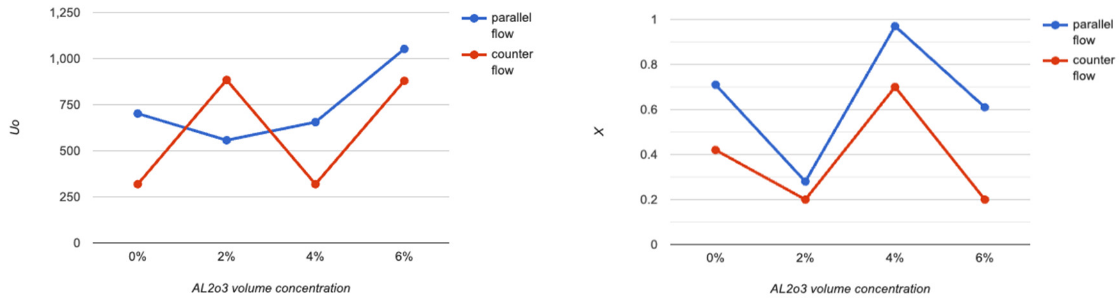

Fig 13: AL_2O_3 volume concentration (vs.) Overall heat transfer coefficient (U_o) (vs.) Effectiveness(X)

The total heat transfer coefficient and effectiveness values are calculated at certain concentrations of nanofluids, and they are shown to be unstable, may be because of Agglomeration of nanoparticles changed the thermophysical characteristics, sedimented the fluid, and interfered with the surface interface between the nanofluid and the heat exchanger.

Prediction of Overall heat transfer coefficient and Effectiveness using Machine Learning algorithms:

In machine learning algorithm, Low error indicates that the model's forecasts closely match actual results, which improves the model's usefulness and reliability in practical applications. On the other hand, a high error rate may result in predictions that are not correct, which would reduce the algorithm's efficacy and maybe make it useless for the intended use.

MODEL	MEAN SQUARE ERROR	MEAN ABSOLUTE ERROR
Decision tree	0.000100	0.00500
Random forest	0.000101	0.00525

Table 5: Mean Absolute Error and Mean square Error

In this investigation, the decision tree algorithm demonstrated superior performance compared to random forest as per above table (5.2). Therefore, the Decision Tree algorithm in machine learning provides clear decision-making pathways resulting in the best overall results.

V. CONCLUSION

Using alumina nano fluid to increase the shell and tube heat exchanger's performance, Experimental research has been done on nano fluid in both parallel and counterflow scenarios. Experimental calculations were used to determine the total heat transfer coefficient and effectiveness for both situations at all volume concentrations of the nanofluid.

The following significant outcomes of this work were noted:

1. When compared to flow conditions, parallel flow Effectiveness is higher than counter flow condition.

2. If the volume concentration of Nano fluid increases, the overall heat transfer coefficient also increases.
3. Highest overall heat transfer coefficient is calculated for parallel flow condition at 6% volume concentration is 1052.49 W/m2 K and Effectiveness is calculated for parallel flow condition at 4% volume concentration is 0.97. The Nano fluid has an overall heat transfer coefficient and effectiveness that surpasses 1.5 times that of the basic liquid.
4. It was concluded that the decision tree algorithm is the best machine learning algorithm which predicts the overall heat transfer coefficient and effectiveness with minimum error. MSE is 0.000100 and MAE is 0.00500.
5. Overall heat transfer coefficient effectiveness prediction can help in better working of shell and tube heat exchanger
6. It was concluded that exploratory data analysis helped a lot to understand the data, which is very helpful in the selection of suitable machine learning model.

FUTURE SCOPE:

An attractive option for the future is the use of hybrid nanofluids in heat transfer applications as an alternative to metal oxide nanofluids. The research may be able to provide greater stability, increased thermal conductivity, and customized features for certain heat exchanger designs by experimenting with different nanoparticle combinations. This invention might lead to improved sustainability and efficiency in thermal management systems and future heat exchanger generations with more performance and adaptability.

Incorporating Genetic Algorithms (GA) into the project instead of decision trees and random forest algorithms enables exploration of evolutionary optimization methods for enhanced model performance and flexibility. This adaptation could lead to increased forecast accuracy, especially in dynamic and complex heat transfer systems, paving the way for advancements in predictive modeling and optimization within the field.

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