



# Article Machine Learning for Prediction of Heat Pipe Effectiveness

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**Abstract:** This paper details the selection of machine learning models for predicting the effectiveness of a heat pipe system in a concentric tube exchanger. Heat exchanger experiments with methanol as the working fluid were conducted. The value of the angle varied from  $0^{\circ}$  to  $90^{\circ}$ , values of temperature varied from  $50 \,^{\circ}$ C to  $70 \,^{\circ}$ C, and the flow rate varied from 40 to 120 litres per min. Multiple experiments were conducted at different combinations of the input parameters and the effectiveness was measured for each trial. Multiple machine learning algorithms were taken into consideration for prediction. Experimental data were divided into subsets and the performance of the machine learning model was analysed for each of the subsets. For the overall analysis, which included all the three parameters, the random forest algorithm returned the best results with a mean average error of 1.176 and root-mean-square-error of 1.542.

Keywords: heat pipe; exchanger; machine learning; effectiveness

# 1. Introduction

Heat pipes are utilized in various products, such as electronics, solar collectors, and heat exchangers, to remove/transfer heat away from the system. Heat pipe techniques have been successfully implemented in most industry applications [1,2]. Heat pipe systems have also been successfully implemented in automobiles for exhaust gas recovery [3]. Usage of heat pipes with environmentally friendly refrigerants has also been reported [4]. The loop heat pipe was used for spacecraft applications and heat transmissibility was considerably increased in this experimentation [5].

Kempers et al. [6] analysed the wicks in the form of mesh in copper heat pipes, and it was reported that mesh layer increase led to better performance. Lower thermal resistance using deionised water was reported by [7]. Filling ratio, inclined angles, number of turns and heat input were tested in various articles, and it was reported that a 50% filling ratio gives maximum performance [8,9].

The performance of heat pipes in satellite applications was investigated and it was reported that minimum thermal resistance was observed when ammonia was used [10]. Numerical studies were reported on various models, and they have shown good agreement with the experimental results [11,12]. Numerical studies using a Navier–Stokes equation



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**Copyright:** © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). have also been successfully used for the modelling of heat pipe performance [13]. The thermal energy storage system was analysed by inserting numerous heat pipes among a heat-carrying fluid [14].

The gravitational effect of the heat pipe, wick structure and working fluid shows improvement in results [15–19]. The heat pipes were studied with various angles, wick constructions and operational fluids [20–23]. In a similar study, the highest heat transfer coefficient at  $60^{\circ}$  and a 50% fill ratio was reported [24]. In studies involving pulsating HP with DI water, it was reported that the lowest thermal resistance of 0.077 K/W was achieved at inclined angles [25].

Traditionally, statistical and heuristic techniques have been used by researchers for the development of such prediction models. Traditional methods rely on the method of generating a relational equation, and this model may not fit the entire data points correctly, leading to non-uniform prediction. Machine learning is the newer technique, which allows to us to obtain a better representation of the process as it helps to identify tricky correlations that may exist within the dataset. ML methods develop patterns for prediction rather than developing a single equation, which further leads to much better flexibility in prediction. The development of prediction and optimization models is a better way of understanding any mechanical system as it is used as a reference for future researchers and industry experts as a means of better understanding the process. Machine learning (ML) methods and techniques have been reported in various areas of manufacturing in an attempt to implement Industry 4.0 [26]. ML has also been used as a tool for manufacturing diagnostics [27] and this is also an advanced data analytics solution [28]. ML application has also been reported by researchers in many thermal-based applications in predicting the performance of fins [29] and the air injection effect [30] in heat exchangers. A detailed review [31] shows how ML methods have been vastly adopted in various heat exchanger processes for the prediction of different performance indicators.

Based on the literature it was observed that ML modelling for heat pipe exchangers with methanol as a working fluid is an area which needs attention. Hence, this article depicts the process for the development of an ML model that can model the effectiveness of the heat exchanger process. Multiple models are developed, and they are further compared to select the best among them. The algorithms are implemented through the WEKA open-source software, which contains the algorithms for various ML methods [32,33].

# 2. Materials and Methods

# 2.1. Fabrication

The heat pipe is fabricated and substitutes the concentric tube of the traditional heat exchanger, as shown in Figure 1. Copper material is employed for the heat pipe, and iron, which is galvanized, is employed for the shell. The total pipe length is 1000 mm, in which 700 mm is inserted inside the shell side of the evaporator section and 300 mm at the condenser section. The diameter of the heat pipe is 19 mm and 17 mm at the outer and inner edges, respectively. The evaporator and condenser shell have diameters of 50 mm and 35 mm, respectively. The total length of the evaporator and condenser shell section is 1000 mm, respectively. Two fluid tanks are fabricated for hot and cold fluid sections. The hot fluid tank (5 L) has an immersion electric heater with a 2000 W capacity. Two rotameters with a capacity of 3 LPM are used for measurement and flow control. The temperatures are measured using thermocouples at all points of the heat pipe heat exchanger.

## 2.2. Experimental Procedure

For both investigations, methanol is used. Methanol is charged with fill ratios of fifty per cent of the evaporator zone volume. Thermophysical properties of the working fluid are described in Table 1 [28]. The minimum tilt angle is set at  $0^{\circ}$  (horizontal) and the maximum tilt angle is set at  $90^{\circ}$  (vertical). The angle varied in increments of  $10^{\circ}$ . The mass flow rate is set at a minimum value of 40 L per hour and a maximum of 120 L per hour.

The intermediate values for mass flow rate that are used in the experiment are 60, 80 and 100 L per hour. Similarly, the maximum value of the set temperature is 70 °C and the minimum value of temperature is 50 °C. The intermediate values of temperature at which the other experiments are conducted are 55 °C, 60 °C and 65 °C. The various parametric levels chosen for the experiment are described in Table 2. The experiments are carried out with each combination of the parameter levels, leading to a total of 250 experiments. The effectiveness of each of the settings is measured and based on this database the ML model is executed.



Figure 1. Schema of the concentric tube heat pipe heat exchanger.

	Table 1. Thermo	-physical	properties	of wo	rking	fluid
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Properties	Methanol
Boiling point	65 °C
Melting point	−97.9 °C
Latent heat of evaporation ( $\lambda$ )	1055 kJ/kg
Density of liquid ( $\rho_l$ )	792 kg/m <sup>3</sup>
Density of vapour ( $\rho_v$ )	$1.47 \text{ kg/m}^3$
Thermal conductivity of liquid (k <sub>l</sub> )	0.201 W/m °C
Vapor pressure (at 293 K)	12.87 kPa
Viscosity of liquid ( $\mu_l$ )	$0.314 imes10^{-3}~\mathrm{Ns/m^2}$
Surface tension of liquid $(\sigma)$	$1.85 imes10^{-2}~\mathrm{N/m}$
Molecular weight (M)	32 g/mol
Specific heat ratio ( $v_v$ )	1.33

Table 2. Parametric levels used in experiment.

S. No	Factors	Minimum	Maximum	Mean	Std-Dev
1	Angle (A)	0	90	45	28.78
2	Mass flow rate (MF)	40	120	80	28.341
3	Temperature (T)	50	70	60	7.085
4	Effectiveness (Methanol)	6.84	38.98	20.13	6.177

## 2.3. Machine Learning Model

The prediction of the effectiveness of the heat pipe system employing methanol is discussed in this section. Effectiveness relies upon angle, mass flow rate and temperature. The objective of this analysis is to predict the effectiveness through various ML algorithms and to identify the best performing algorithm among them. Angle, mass flow rate and temperature are the inputs that affect the effectiveness of the process. These are the factors considered in the ML model. ML is the possibility in which a PC program can learn and conform to new data without human intervention. ML assesses a relationship between

the factors and the output. ML methods are classified into five classes, namely: functions, lazy learning algorithms, meta-learning algorithms, rule-based algorithms and tree-based learning algorithms. The steps involved in the ML process are depicted in Figure 2.



Figure 2. Steps involved in machine learning.

## 2.4. Identification and Pre-Processing of the Dataset

Pre-processing is an interaction of cleaning the missing or crude information. The information is gathered through real-time data and is changed over to a spotless informational index. These are a portion of the fundamental pre-processing procedures that can be utilized to change over crude information. Pre-processing is used to normalize the data as the various data fall in different data categories and there is a need to create uniformity among the data for better interpretation by the machine learning algorithms.

## 2.5. Separation, Training and Testing

Separation of datasets is performed to decide the best subset. The best subset is a list of capabilities, which demonstrates the best exhibition in expectation exactness. Hypothetically, the best subset can be found by assessing every one of the potential subsets. Training is carried out by analysing every subset under 30 algorithms. Each algorithm is applied to each subset. After training each subset in each algorithm, the output predictions are tested and noted. Then, mean absolute errors and root-mean-square errors of all subsets are also tested and noted.

# 2.6. Evaluation of Our Model

The MAE (mean average error) and RMSE (root-mean-square error) of a subset that has fewer errors is taken as the best regression method and best subset, and their output predictions are the best predictions of the dataset.

## 2.7. Dataset Description

The set or the assortment of information obtained through experimentation is known as a dataset. The dataset's information is arranged such that there are a set of values which represent the input and output factors. The dataset utilized in this examination, which comprises instances, attributes, info factors and an objective variable, was gathered over a multi-month time. Figure 3 shows the scatter plot of the various factors against the effectiveness.

## 2.8. Dataset Separation

Here, the dataset is divided into several subsets. The separate datasets are then saved in CSV format. After separation, the loading of each subset is completed. After loading, basic statistics such as minimum values, maximum values, mean and standard deviation are calculated. The various subsets that can be generated in this experiment are listed in Table 3. For each of the subsets, the prediction model is trained and tested on all possible regression algorithms available. In similar ways, all the subsets are tested on all regression methods.



Figure 3. Scatter plot of parameters and responses.

**Table 3.** Determination of the subsets.

S. No.	Subsets	Α	MF	Т
1	А	1	0	0
2	MF	0	1	0
3	Т	0	0	1
4	A-MF	1	1	0
5	A-T	1	0	1
6	MF-T	0	1	1
7	A-MF-T	1	1	1

In artificial intelligence-based regression examination, a significant strategy is to show the interrelation between target and factors. Regression examination makes us perceive how the change in independent variables affects the dependent variables in any process. Regression algorithms are classified into functions, lazy learning algorithms, meta-learning algorithms, rule-based algorithms and tree-based algorithms. Full forms of all algorithms are shown in Table 4.

## 2.9. Precision of Prediction

The prediction precision of every machine learning regression strategy is utilized to assess the difference between the real and anticipated qualities. The prediction precision is assessed through indices such as mean absolute error (MAE) and root-mean-square error (RMSE). An error can be defined as the difference between the experimental and predicted value. Mean absolute error (MAE) is calculated by taking the average of the absolute error and is shown in Equation (1).

$$MAE = |a1 - c1| + |a2 - c2| + \dots + |an - cn| / n$$
(1)

Root-mean-square Error (RMSE) is also often utilised for determining the closeness of the predicted value with the actual value, and the formula used is shown in Equation (2).

RMSE = 
$$\sqrt{\frac{\sum_{i=1}^{n} (a_n - c_n)^2}{n}}$$
 (2)

Table 4. Full forms of all algorithms.

Categories	Algorithms	Full-Form
	SLR	Simple Linear Regression
	LMs	Least Median Square
	GP	Gaussian Processes
Functions	MLP	Multilayer Perceptron
	RBFN	Radial basis Function Network
	RBFR	Radial basis Function Regressor
	SMOREG	Support vector machine Optimizer Regression
	IBK	Instance Based Learner K
Lazy	K star	K Star
	LWL	Locally Weighted Learning
	AR	Additive Regression
	BREP	Bagging Reduced Error Pruning
	MS	Multi Scheme
Meta	RC	Random Committee
	RFC	Random Filtered Classifier
Meta	RSS	Random Subspace
	RBD	Random By Discretization
	STACKING	Stacking
	VOTE	Vote
	WIHW	Weighted Instances Handled Wrapper
	DT	Decision Table
Rules	M5R	M5R
	ZEROR	ZERO R
	DS	Decision Stump
	M5P	M5P
Trees	RF	Random Forest
	RT	Random Tree
	REP TREE	Reduced Error Pruning
Misc.	IMC	Instance Mapped Classifier

# 3. Results and Discussion

The best subset is selected by analysing the mean values of all tested algorithms. The best algorithm is found by analysing all of the mean absolute errors and root-mean square errors. Table 5 shows the result of the machine learning model when only one parameter is taken into consideration. The three parameters are run separately and the results are tabulated. It can be observed that angle has the least error observed at an MAE of 3.671 and RMSE of 4.417. These lowest errors are obtained through the random forest algorithm. The next model is executed with two-parameter subsets. The three different combinations of the input parameters were run separately and the results are reported in Table 6. It can be observed that the angle–temperature combination has the least error as the MAE value is 2.373 and the RMSE value is 2.921. The lowest errors are obtained through the additive regression method.

A box plot for the RMSE is also developed to better understand the variation in the data. Figure 4 shows the box plot of single-parameter subset performance. Angle displayed the least RMSE with a value of 4.415; hence, it was selected as the best performing subset. Similarly, Figure 5 shows the box plot of two-parameter subset performance. The minimum RMSE value of 2.921 was obtained for the angle–temperature subset and thus was selected as the best-modelled subset for two parameters.

SUBSETS		Α		Ν	1F	Т		
Categories	ALGORITHMS	MAE	RMSE	MAE	RMSE	MAE	RMSE	
	SLR	4.972	6.139	5.075	6.212	4.456	5.660	
	LR	4.972	6.139	5.053	6.199	4.456	5.660	
	LMs	4.974	6.421	5.080	6.229	4.432	5.686	
Functions	MLP	4.986	6.126	5.179	6.280	4.372	5.654	
	GP	5.063	6.180	5.068	6.203	4.776	6.023	
	RBFN	4.914	6.061	5.058	6.195	4.462	5.601	
	RBFR	4.100	4.951	4.761	5.847	4.135	5.271	
	SMOREG	4.983	6.248	5.093	6.263	4.405	5.704	
	IBK	3.673	4.415	4.761	5.847	4.135	5.271	
	Kstar	4.208	5.166	4.790	5.882	4.208	5.304	
	LWL	3.900	4.691	4.815	5.903	4.136	5.274	
	AR	3.728	4.475	4.764	5.851	4.131	5.268	
	BREP	3.701	4.458	4.793	5.878	4.125	5.284	
	MS	5.053	6.199	5.053	6.199	5.053	6.199	
	RC	3.673	4.415	4.761	5.847	4.135	5.271	
Mata	RFC	3.673	4.415	4.739	5.847	4.135	5.271	
Meta	RSS	3.707	4.446	4.783	5.871	4.131	5.274	
	RBD	3.702	4.410	4.864	5.944	4.151	5.228	
	STACKING	5.053	6.199	5.053	6.199	5.053	6.199	
	VOTE	5.053	6.199	5.053	6.199	5.053	6.199	
	WIHW	5.053	6.199	5.053	6.199	5.053	6.199	
	DT	3.673	4.415	4.761	5.847	4.135	5.271	
Rules	M5R	3.721	4.485	4.851	6.000	4.102	5.229	
	ZEROR	5.053	6.199	5.053	6.199	5.053	6.199	
	DS	4.567	5.613	4.979	6.065	4.152	5.317	
	M5P	3.843	4.632	4.873	5.997	4.115	5.229	
T	RF	3.671	4.417	4.770	5.859	4.136	5.271	
Trees	RT	3.673	4.415	4.761	5.847	4.135	5.271	
	REP TREE	3.683	4.427	4.818	5.876	4.195	5.333	
	IMC	5.053	6.199	5.053	6.199	5.053	6.199	

 Table 5. Subsets with one parameter—Performance.



Figure 4. Box plot for RMSE in single-parameter subset performance.



Figure 5. Box plot for RMSE in two-parameter subset performance.

	SUBSETS	А	-MF	А	. <b>-</b> T	MF-T		
Categories	ALGORITHMS	MAE	RMSE	MAE	RMSE	MAE	RMSE	
	SLR	4.972	6.139	4.456	5.660	4.456	5.660	
	LR	4.972	6.139	4.338	5.589	4.456	5.660	
	LMs	4.998	6.460	4.301	6.044	4.442	5.698	
Functions	MLP	5.003	6.141	4.281	5.597	4.471	5.729	
	GP	5.061	6.187	4.315	5.606	4.571	5.827	
	RBFN	5.101	6.216	4.488	5.636	4.787	5.871	
	RBFR	4.557	5.608	3.676	4.791	3.883	4.971	
	SMOREG	5.020	6.297	4.240	5.789	4.434	5.739	
	IBK	3.971	4.451	2.631	3.062	3.877	5.081	
	Kstar	4.125	4.917	3.236	4.116	3.963	5.024	
	LWL	4.016	4.814	3.336	4.259	4.086	5.233	
	AR	3.463	3.961	2.373	2.921	3.693	4.842	
	BREP	3.783	4.225	2.498	2.935	3.911	5.100	
	MS	5.053	6.199	5.053	6.199	5.053	6.199	
	RC	3.971	4.451	2.631	3.062	3.877	5.081	
Mate	RFC	3.971	4.451	2.655	3.152	3.877	5.081	
Meta	RSS	3.986	4.786	3.331	4.175	4.287	5.319	
	RBD	3.766	4.306	2.578	3.075	3.761	4.951	
	STACKING	5.053	6.199	5.053	6.199	5.053	6.199	
	VOTE	5.053	6.199	5.053	6.199	5.053	6.199	
	WIHW	5.053	6.199	5.053	6.199	5.053	6.199	
	DT	3.798	4.508	2.631	3.062	3.877	5.081	
Rules	M5R	3.732	4.409	2.606	3.178	4.064	5.195	
	ZEROR	5.053	6.199	5.053	6.199	5.053	6.199	
	DS	4.567	5.613	4.152	5.317	4.152	5.317	
	M5P	3.840	4.559	2.927	3.666	4.056	5.168	
Trace	RF	3.956	4.419	2.627	3.052	3.877	5.075	
Trees	RT	3.971	4.451	2.631	3.062	3.877	5.081	
	REP TREE	3.689	4.286	2.600	3.120	4.073	5.221	
	IMC	5.053	6.199	5.053	6.199	5.053	6.199	

Table 6. Subsets with two parameters—Performance.

Finally, the model is run with three-parameter subsets and the entire combination of factors is taken into consideration. Here, there is only a single combination of all the parameters. The results from the various machine learning algorithms are listed below in Table 7. The random forest algorithm provided the least errors as the values reported for MAE and RMSE were 1.1755 and 1.5422, respectively.

From the subset analysis, further classification is carried out by extracting the best models from each subset. The subsets with the least errors are listed below in Table 8. Hence, the table represents the best models in each of the subset categories. The mean of the MAE and the RMSE errors for each of the categories is taken and it is observed that the lowest errors are obtained through the random forest algorithm. The MAE and the RMSE values obtained are 2.491 and 3.004, respectively.

Figure 6 shows the interface of the Weka software, and it denotes the various statistics such as time taken to build the model, the number of iterations, correlation coefficient, mean absolute error and the root-mean-square error.

	SUBSETS	A-N	/IF-T
S. No.	ALGORITHMS	MAE	RMSE
1	SLR	4.4564	5.6602
2	LR	4.3383	5.5886
3	LMs	4.2658	5.9911
4	MLP	4.2088	5.691
5	GP	4.3014	5.5754
6	RBFN	4.8086	5.8918
7	RBFR	3.7402	4.8737
8	SMOREG	4.2041	5.7579
9	IBK	4.3151	6.6209
10	Kstar	3.2171	4.2561
11	LWL	3.5059	4.4872
12	AR	1.6308	2.0891
13	BREP	1.5975	2.0988
14	MS	5.053	6.1989
15	RC	1.3252	1.7054
16	RFC	4.6006	6.9647
17	RSS	2.5109	3.1017
18	RBD	1.9612	2.4249
19	STACKING	5.0530	6.1989
20	VOTE	5.0530	6.1989
21	WIHW	5.0530	6.1989
22	DT	2.6309	3.0623
23	M5R	2.7984	3.6392
24	ZEROR	5.0530	6.1989
25	DS	4.1520	5.3165
26	M5P	2.9438	3.7524
27	RF	1.1755	1.5422
28	RT	1.8456	2.4296
29	REP TREE	1.9963	2.5834
30	IMC	5.0530	6.1989

 Table 7. Subsets with one parameter—Performance.

Preprocess Classify Cluster Associa	te Select attributes Vi	sualize			
Classifier					
Choose RandomForest -P 100 -I 100	-num-slots 1 -K 0 -M 1.0 -	V 0.001 -S 1			
Test options	Classifier outpu				
Use training set       Supplied test set       © Cross-validation       Folds       10       Parcentage split       % 66       More options	Scheme: A Relation: A Instances: 2 Attributes: 4 S Test mode: 1	veka.classifiers. , MF, T methanol 50 ingle lass flow rate 'emperature iffectiveness 0-fold cross-val	rees.RandomForest -F 100 -I 100 -num-s dation	lots 1 -R 0 -M 1.0 -V 0.001 -S 1	
(Num) Effectiveness	Classifier RandomForest	model (full train	ing set) ====		
Result list (right-click for options	Bagging with 10	0 iterations and	base learner		
	Weka.classifier	s.trees.RandomTr	e -R 0 -M 1.0 -V 0.001 -S 1 -do-not-cn seconds	eck-capabilities	
	=== Cross-valid	lation ===			2
	Correlation coe Mean absolute e Root mean squar	fficient rror ed error	0.9729 1.1755 1.5422		, ,
Status					
ок					Log 🛷 X

Figure 6. Random forest algorithm.

Calaaria	SUBSETS	A	L	A	Т	A-N	1F-T	Me	an
Categories	ALGORITHMS	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
	SLR	4.972	6.139	4.456	5.660	4.456	5.660	4.628	5.820
	LR	4.972	6.139	4.338	5.589	4.338	5.589	4.549	5.772
	LMs	4.974	6.421	4.301	6.044	4.266	5.991	4.514	6.152
	MLP	4.986	6.126	4.281	5.597	4.209	5.691	4.492	5.805
	GP	5.063	6.180	4.315	5.606	4.301	5.575	4.560	5.787
Functions	RBFN	4.914	6.061	4.488	5.636	4.809	5.892	4.737	5.863
	RBFR	4.100	4.951	3.676	4.791	3.740	4.874	3.839	4.872
	SMOREG	4.983	6.248	4.240	5.789	4.204	5.758	4.476	5.931
	IBK	3.673	4.415	2.631	3.062	4.315	6.621	3.540	4.699
	Kstar	4.208	5.166	3.236	4.116	3.217	4.256	3.554	4.513
	LWL	3.900	4.691	3.336	4.259	3.506	4.487	3.581	4.479
	AR	3.728	4.475	2.373	2.921	1.631	2.089	2.577	3.161
	BREP	3.701	4.458	2.498	2.935	1.598	2.099	2.599	3.164
	MS	5.053	6.199	5.053	6.199	5.053	6.199	5.053	6.199
	RC	3.673	4.415	2.631	3.062	1.325	1.705	2.543	3.061
	RFC	3.673	4.415	2.655	3.152	4.601	6.965	3.643	4.844
Meta	RSS	3.707	4.446	3.331	4.175	2.511	3.102	3.183	3.908
	RBD	3.702	4.410	2.578	3.075	1.961	2.425	2.747	3.303
	STACKING	5.053	6.199	5.053	6.199	5.053	6.199	5.053	6.199
	VOTE	5.053	6.199	5.053	6.199	5.053	6.199	5.053	6.199
	WIHW	5.053	6.199	5.053	6.199	5.053	6.199	5.053	6.199
	DT	3.673	4.415	2.631	3.062	2.631	3.062	2.978	3.513
Rules	M5R	3.721	4.485	2.606	3.178	2.798	3.639	3.042	3.768
	ZEROR	5.053	6.199	5.053	6.199	5.053	6.199	5.053	6.199
	DS	4.567	5.613	4.152	5.317	4.152	5.317	4.290	5.415
	M5P	3.843	4.632	2.927	3.666	2.944	3.752	3.238	4.017
	RF	3.671	4.417	2.627	3.052	1.176	1.542	2.491	3.004
irees	RT	3.673	4.415	2.631	3.062	1.846	2.430	2.717	3.302
	REP TREE	3.683	4.427	2.600	3.120	1.996	2.583	2.760	3.377
	IMC	5.053	6.199	5.053	6.199	5.053	6.199	5.053	6.199

**Table 8.** Selection of the best performances from the different subsets.

The scatter plots of the predicted versus the experimental values for the various analyses are shown in Figures 7–9. Figure 7 represents the scatter plot for predicted versus actual values for one-parameter subset. Since only one subset is considered, it can be observed that there is a larger amount of scatter. It is observed that when two-parameter subsets are considered, the scatter plot is more even with less deviation overall as depicted in Figure 8. In Figure 9, all the parameters are considered, and the scatter plot shows a more even plot. It can be concluded that when all the factors are considered, the machine learning model provides a much better model. Hence, it can be confirmed that the machine learning model provides the best solution when all the factors are considered for the analysis. This also indicates that all the factors have a significant effect on the output.

The performances of the different algorithms that have been described in this study are best illustrated in Figure 10. The figure shows that the random forest algorithm has the best performance when the system comprising all the three factors is considered as a whole.

From the above analysis, we can understand that random forest is the best regression strategy (best algorithm) for predicting the effectiveness of a heat pipe system when methanol is used as the working fluid. Random forest builds multiple decision trees and merges them to create a more accurate and stable prediction. Predicted vs. actual values are compared by taking 15 to 20 random values from the respective outputs of their best regression methods. Figure 11 plots the predicted vs. the experimental values and the marked green area indicates that the deviation is acceptable. Here, the best regression

method for effectiveness is random forest. A correlation coefficient of 0.9729, MAE of 1.1755, and RMSE of 1.5422 was obtained as the result of the analysis.



Figure 7. Plot of predicted and actual values for one-parameter subset.



Figure 8. Plot of predicted and actual values for two-parameter subset.



Figure 9. Plot of predicted and actual values for three-parameter subset.



Figure 10. MAE and RMSE of the different machine learning models.



Figure 11. Actual vs. predicted effectiveness.

# 4. Conclusions

The identification of the best machine learning model for a heat exchanger process is discussed in this article. Heat exchanger experiments with methanol as the working fluid are conducted with consideration of various factors such as angle, temperature and mass flow rate and the effectiveness of each of the experiments is measured. The value of the angle is varied from 0 to 90 in increments of 10. Values of temperature are varied in increments of 5, starting from 50 to 70. Mass flow rate is varied from 40 to 120 in increments of 20. The experiments are conducted for each of the combinations of the input parameters and the effectiveness is measured for each trial. From the experiment data, a machine learning model is developed to identify the algorithm which best fits the experiment. Thirty algorithms were taken into consideration and the experimental values were analysed for each of the algorithms. The experimental data were divided into subsets and the performance of the machine learning model was analysed for each of the subsets. Single-parameter subset analysis revealed that angle had the most correlation with effectiveness as the MAE (3.671) and RMSE (4.417) were minimum. For the singleparameter analysis, the random forest algorithm was found as the best fit. Similarly, for the two-parameter subset, it was inferred that the angle-temperature combination had the most correlation with effectiveness and the MAE and RMSE were 2.373 and 2.921, respectively. For this, the additive regression method was identified as the best machine learning model. For the overall analysis that included the all three parameters, the random forest algorithm returned the best results with an MAE of 1.176 and RMSE of 1.542. The results show that machine learning models can be successfully used for representing the physical experiments in a numerical model. With the presence of increasing databases, more such studies can be conducted in the future to create robust databases that best depict the process.

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