Heat transfer performance and prediction of open pulsating heat pipe for self-cooling cutting tool

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Received: 28 April 2022 / Accepted: 14 July 2022 / Published online: 25 July 2022
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Abstract
The pulsating heat pipe (PHP) can be used to transfer massive heat to reduce the thermal damage to the cutting tool when machining difficult-to-cut materials. To select a better open PHP, the heat transfer performance was experimentally investigated in this study. The operating characteristics of different types of working fluids under different heat flux were analyzed compared with the closed PHP. Visual experiments were established to verify the experimental characteristics. The effects of heat flux, length, ratio of inner/outer diameter, and inclination angle on equivalent thermal resistance were analyzed. Based on the experimental data and four boosting integrating learning methods, a model for heat transfer performance prediction was proposed. The prediction model based on the CatBoost method had better goodness-of-fit and the best prediction effect. The $R^2$, MAPE, and RMSE of the validation set were the best, which are 0.9258, 7.2564, and 0.1057 respectively. In addition, the contribution of input parameters to the output results was evaluated, while $L$, $D_i/D_o$, and $Pr$ were the top three variables. Sub-tree structures used to explain the prediction model were also presented. This proposed prediction model can be used to select the most suitable open PHP before designing PHP self-cooling tools.

Keywords  Open pulsating heat pipe · Heat transfer performance · Boosting integrated learning · Prediction model

Abbreviations

| Abbreviation | Description |
|--------------|-------------|
| $K_a$        | Karman number |
| $J_a$        | Jakob number |
| $M_o$        | Morton number |
| $P_r$        | Prandtl number |
| $R$          | Thermal resistance [°C/W] |
| $D$          | Diameter [mm] |
| $h$          | Heat transfer coefficient [W/m²*°C] |
| $L$          | Length [mm] |
| $Q$          | Heat flux power [W] |
| $q$          | Heat flux density [W/m²] |
| $S$          | Surface area [mm²] |
| $T$          | Temperature [°C] |

Greek symbols

| Symbol | Description |
|--------|-------------|
| $\lambda$ | Heat conductivity coefficient [W/m² * °C] |
| $\alpha$ | Inclination angle [radian] |

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1 Introduction

Nowadays, massive heat concentration is regarded as one of the most serious problems to be solved in the traditional machining process, which has a negative impact on the stability of the machining process and the surface quality of the tool and workpiece [1]. The emergence and development of heat pipes provide an opportunity to transfer heat from the tool-workpiece contact zone. Heat pipe is a kind of equipment designed by using the characteristics of heat absorption or release during liquid and vapor phase transformation. The process of evaporation of liquid working fluids and liquefaction of steam in condensing section is repeated continuously to achieve the effect of heat conduction without the need for additional external energy [2]. Pulsating heat pipe (PHP) is a kind of heat pipe with good application prospect,
which has a structure of a thinner pipe and a plurality of alternately continuous evaporation section at the bottom, adiabatic section in the middle, and condensation section at the top [3]. Due to the different channel layouts, the PHP can be classified as open PHP and closed PHP with or without a one-way valve [4]. At present, PHP has been already widely used in traditional machining fields. For example, Wu et al. [5, 6] combined the open PHP with the turning tool insert or holder, which reduced the cutting temperature of the tool nose by about 10% and improved the cutting life of the tool by about 20–30%. Qian et al. [7, 8] positioned multiple single-loop closed PHPs in grinding wheels and abrasive-milling tools. The results of this study represented that the cooling effect of the PHP in the grinding and milling process was better than that of the coolant.

Most of the researches were carried on the closed PHP, due to its better heat transfer performance and lower thermal resistance [9]. What characteristic open PHP and closed PHP have in common is that bubbles and liquid columns form unstable pulsating flow with random direction due to the action of surface tension, which is called “Taylor bubble flow” [10]. Another reason to choose closed PHP instead of open PHP is that, with a closed channel, the liquid column and bubbles have a smoother movement and more obvious visualization results [11]. At present, the variable research of closed PHP focuses on the type of working fluids, filling ratio, heat flux power, and inclination angle where it is not necessary to fabricate massive PHPs [12–14]. Because the production process of closed PHP is complicated, most of the research can only produce a limited number of PHPs before the experiment.

Many scholars have obtained the influence of geometrical parameters and experimental parameters of PHPs on heat transfer performance through experimental research on heat transfer performance. Feng et al. [15] added check valves to PHPs to produce one-way circulating flow of working medium. Compared with the ordinary open PHP, the heat resistance of the PHP with check valve is reduced by 25%. Xu et al. [16] studied the effects of seven working fluids with different filling ratios on the heat transfer performance. It was found that when two incompatible working fluids were used, the working fluids could form an emulsion during oscillation, which promoted heat transfer between the two working fluids. In addition, at low heating power, gravity had an important effect on the heating performance. The heat transfer performance of PHPs was the best when the inclination angles were higher (45° and 60°). Singh and Kumar [17] studied the heat exchange effect of PHPs with hexanol self-wetting liquid and DI water as liquid working medium and also studied the parameters of filling ratio of 10%, 50%, and 90% and heat flux power input of 20–140 W. In addition, the thermal physical properties of working medium such as surface tension, contact angle, and conductivity were studied from the perspective of temperature change. The higher filling ratio was favorable to the fall from condensation to evaporation of working medium.

However, open PHP is more convenient to manufacture and install; thus, it is more suitable for the need to use large amounts of PHPs. When it is necessary to combine the PHP with the cutter of the traditional processing process in batches or take the length or the diameter of PHP as the research variables, more experimental costs and time can be saved by using open PHP. Few researchers concentrated on open PHP nowadays. The researches about the influence of various variables on open PHP were not comprehensive. Taslimifar et al. [18] studied the influence of working fluid, heat flux power, inclination angle, and other variables on the start-up performance and steady-state performance of open PHPs. The influence of sensible heat, finned or not, and solid nanoparticles were studied in the literature [19–21]. Therefore, there are no geometric parameters such as length and diameters to study the performance of open PHP. The influence laws obtained by open PHPs should be compared with those by closed PHPs. In addition, this study mainly focused on PHPs that can be combined with cutting tools; thus, a new range of variables is needed to be defined to fit the cutting tool structure and cutting process.

With the great progress in the research of the heat transfer performance of PHP, many researchers seek a specific and widely accepted prediction method, to reduce the test for the performance of different PHP caused by repeated experiments. The prediction method was based on the experimental data and influence laws of various factors. Ling et al. [22, 23] attempted to establish a fitting formula to predict thermal performance, introduced with variables including heat flux, geometric parameters, dynamic viscosity, and dimensionless parameters such as \( Mo \), \( Ja \), \( Ka \), and \( Pr \). In recent years, as machine learning algorithms develop continuously, researchers have put forward various numerical prediction methods. The machine learning method can solve the problems of multiple factors, providing a new effective way to predict problems with nonlinear characteristics such as artificial neural network (ANN) [24]. Taking the number of turns, filling ratio, heat flux, inner diameter, and various dimensionless numbers as input parameters and thermal resistance as output parameters, Wang et al. [4, 25] established two neural network models with better MSE and \( R^2 \) values than the fitting formula models. Ahmadi et al. [26] compared the prediction results of four machine learning algorithms and finally found that RBF neural network had the best prediction effect, with \( R^2 \) and RMSE values being 0.9892 and 0.0650, respectively. However, with the increase of data quantity, the goodness-of-fit of the neural network model becomes worse gradually [27, 28]. In addition, due to the differences between geometric parameters, physical parameters, and dimensionless numbers, it is difficult to normalize the dimensionless...
numbers in neural network modeling. Researchers began searching for other effective machine learning algorithms. Qian et al. [29] introduced a prediction model for the thermal resistance of PHPs based on the extreme gradient boosting algorithm (XGBoost). This model can not only predict better than other algorithms but also evaluate the contribution of input parameters and give the subtree structures which can explain the process of the model prediction. XGBoost is a boosting integrated learning method based on decision tree [30]. Other methods in the same category are GBDT [31], LightGBM [32], and CatBoost [33]. Compared with ANN, these algorithms have the advantages of no normalization, more accurate prediction, faster speed, and the approach to explain the model.

Among the prediction models mentioned above, the models in literature [25, 26, 28] can be used directly after obtaining sufficient data, while the models in literature [4, 29] also need to measure the temperature of the evaporation section and Ja number in the experiment as the input variable. Experiments are also needed to predict thermal resistance in that case. The input parameters of each model were not analyzed for correlation to achieve dimensionality reduction. In addition, the neural network model cannot explain the prediction process, whereas the XGBoost method can. Therefore, in addition to investigating the heat transfer performance of open PHP, the problem is how to select a prediction model in which input variables are more convenient to acquire and train, and the prediction model can be interpreted.

In light of these challenges above and comparing the difference with the closed PHP, an experimental platform for measuring the evaporation and condensing temperatures of open PHPs and a prediction model for heat transfer performance of PHPs were established. Heat flux power, length, ratio of inner/outer diameter, type of working mediums, and inclination angle were selected as variables, while equivalent thermal resistance was used to evaluate the heat transfer performance. Based on the experimental results, the effects of different variables on the equivalent thermal resistance of open PHPs were discussed. The performance of four different boosting integrated models, GBDT, XGBoost, LightGBM, and CatBoost, was compared by several evaluation indexes. This prediction model can be used to select open PHPs before designing self-cooling cutting tools.

2 Experimental setup and data processing

2.1 Design of experimental platform

In order to simulate the heat transfer process of PHP during cutting, an experimental platform was established to measure the temperature of the evaporating section and condensing section of open PHP. As is shown in Fig. 1, the experimental platform consisted of several parts.

Firstly, during the cutting process, the cutting heat was mainly concentrated on the cutting insert, so the evaporation section of PHP was installed near the cutting insert. To simulate the generation of cutting heat, the heating device was connected to the evaporation section, and the heat flux of a certain power was provided through resistance wire heating. The electric power load was provided by MESTEK DP305 regulated power supply, and the resistance wire was Ni–Cr heating wire. This part provided a certain amount of heat to the PHP so that it can start operating. Secondly, in order to ensure the heat transfer process of PHP, the condensing section was connected with the air cooling device, which accelerated the heat emission and cooling of the condensing section. The temperature of cold air was about 5–10 °C. The adiabatic section was wrapped with tinfoil paper to achieve the purpose of heat preservation and reduce heat loss. Thirdly, the temperature measuring device, NI DAQ type K thermocouple, was connected to the condensing section and the evaporation section to obtain temperatures. The average temperature of each temperature measuring point was taken, which can be substituted into the calculation of thermal resistance below. The measurement of temperature was processed by software NI LabView. The environment temperature was maintained at about 20 °C.

The experimental platform built according to the schematic diagram is shown in Fig. 2a. In Fig. 2a, open PHPs made of red copper were studied. In order to reduce heat dissipation, insulation barrel was used. In this part, the heat transfer performance of open PHP can be obtained by measuring temperature and calculating thermal resistance. However, only temperature variation or thermal resistance law was not enough to show the heat transfer process of PHP. Therefore, in Fig. 2b, the open PHP made of quartz glass was used to investigate the operating characteristics of working mediums inside the PHP by visualization process, so as to verify the experimental results of heat transfer experiment by combining with the temperature variation or thermal resistance law. The operating characteristics of the working medium were captured by a high-speed camera.

The range of geometrical and physical parameters of open PHP was selected according to the application of cutting tools used for turning. For example, an excessive length will affect the stability of PHP in the cutting process. The length range of PHP installed on the turning tool should not exceed 200 mm because the tool length is about 150–300 mm. The geometrical parameters to be determined were the inner and outer diameters, the length of PHP (distance from the bottom of evaporation section to the top of condensation section), the number of turns, and the shape of cross-sections. The physical parameters to be determined included the type of working mediums in
the PHP and the type of PHP wall material. Other operating parameters to be determined included the filling ratio of the working fluids, heating power, and working angle. Specific parameter selection is shown in Table 1. Since more turns can improve the heat transfer performance of PHP, the number of turns was selected as 3 according to the volume of the cutting tool. The working lengths were 100 mm, 150 mm, and 200 mm. The wall thickness of the PHP was around 0.5 mm, and the outer diameters were 2 mm, 2.2 mm, 2.5 mm, and 3 mm. The filling ratio was 50% for all. Among them, DI water has the highest specific heat capacity, latent heat of vaporization, and surface tension. Ethanol has the lowest boiling point. Al₂O₃ nanofluid has the highest thermal conductivity.

Fig. 1 Schematic diagram of experimental setup for heat transfer performance of open PHP for designing self-cooling cutting tool

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In the process of heat transfer, the temperature of condensing section cannot be kept at a low temperature stably but rises with that of the evaporation section. If two PHPs have different parameters, the same heat flow absorption, and the same temperature difference, then the PHP with a higher overall temperature has the same thermal resistance as the one with a lower overall temperature when using traditional formulas for thermal resistance. Therefore, in this study, the thermal resistance is solved by separating the two sections and adding the thermal resistance of the heat pipe wall.

2.2 Determination of heat transfer performance measurement index

As is shown in Fig. 3, when the parts of the heat pipe are separated and analyzed rather than as a whole, the thermal resistance of several parts can be obtained. The evaporation section, adiabatic section, and condensation section can be regarded as the thermal resistance of working medium ($R_1$, $R_3$, $R_5$) and PHP wall ($R_2$, $R_4$, $R_6$). Since the adiabatic section can be approximately regarded as having no heat exchange, the $R_3$ in the adiabatic section can be regarded as 0. The heat transfer of the adiabatic pipe wall is from the bottom of the heat pipe to the top, and the heat transfer area is very small, so the thermal resistance of pipe wall $R_4$ can be regarded as $\infty$. The thermal resistance of evaporating and condensing sections ($R_1$ and $R_5$) can be calculated from the following equation.

$$R = \frac{T - T_{envir}}{Q}$$

(1)

where $Q$ is the heat flux power. $T$ is the temperature after the steady operation. $T_{envir}$ is the environment temperature. The thermal resistance of tube wall ($R_2$, $R_6$) can be obtained by the following equation [34–36].

$$R_{wall} = \frac{\ln\left(\frac{d_o}{d_i}\right)}{2\pi\lambda L}$$

(2)

where $d_o$, $d_i$, and $L$ are outer diameter, inner diameter and length. $\lambda$ is the heat conduction coefficient. The thermal resistance $R_E$ of single evaporation sections or $R_C$ of single condensation sections can be regarded as the sum of $R$ and $R_{wall}$. In this study, the open PHP was equipped with multiple evaporation and condensation sections, so it can be equivalent to the sum of multiple thermal resistance. After the thermal resistance of the adiabatic section was selected as 0, the equivalent thermal resistance diagram is shown in Fig. 4. The thermal resistance obtained for evaluating the heat transfer performance can be given as follows.

![Figure 2: Experimental setup for open PHP.](image)

**Table 1** Parameters of open pulsating heat pipes

| Parameters         | Values                        |
|--------------------|-------------------------------|
| Heat flux power (W)| 10, 20, 30                    |
| Number of turns    | 3                             |
| Inner/outer diameter (mm) | 1/2, 1.2/2.2, 1.5/2.5, 2/3 |
| Length (mm)       | 100, 150, 200                 |
| Working fluids    | DI water, ethanol, Al₂O₃ nanofluids |
| Charging ratio    | 50%                           |
where \( R_{\text{eff}} \) is the equivalent thermal resistance. Symbol “∥” means parallel connection.

### 3 Building of prediction model

#### 3.1 Algorithm model

The algorithm model in this study adopts the integrated learning method based on decision tree [37]. This section will introduce several Boosting Tree algorithms used in this study.

\[
R_{\text{eff}} = (R_{E_1} \parallel R_{E_2} \parallel R_{E_3}) + (R_{C_1} \parallel R_{C_2} \parallel R_{C_3} \parallel R_{C_4}) 
\]

(3)

3.1.1 Gradient boosting decision tree (GBDT)

GBDT algorithm is a combination of gradient boosting strategy and boosting tree [31]. By fitting the decision tree, the cumulative result of all trees is taken as the final result. When the GBDT regression model is established, an initial regression tree is first trained on the training set, which can be expressed as follows:

\[
h_0(x) = \text{argmin}_c \sum_{i=1}^{m} L(y_i, c)
\]

(4)

where \( y_i \) is the actual output value, \( c \) is the fitting value, \( L(y_i, c) \) is the loss function of both, and \( m \) is the number of samples.

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Fig. 3 Schematic diagram of thermal resistance of heat pipe

Fig. 4 Schematic diagram of thermal resistance of open PHP

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The decision tree fitting function of each round is given by the following function.

\[ h_t(x) = \sum_{j=1}^{J} c_{ij}(x \in R_j) \]  

(5)

where \( c_{ij} \) is the fitting output value of each iteration, \( t \) is the number of iterations, and \( R_j \) is the leaf node of the regression tree.

In order to minimize the loss function, GBDT uses the negative gradient of the loss function to fit the approximate value of the loss of this round. The negative gradient of the loss function of the \( \text{ith} \) round can be expressed as the following function.

\[ r_i = -\frac{\partial L(y, h_{i-1}(x))}{\partial h_{i-1}(x)} \]  

(6)

Then, \( r_i \) can be used to fit the new regression tree, and the best output value \( c_{ij} \) can be fitted at the leaf node of each decision tree to minimize the loss function.

\[ c_{ij} = \arg\min_c \sum_{x \in R_j} L(y, h_{i-1}(x) + c) \]  

(7)

\( j = 12 \ldots \ldots J \)

where \( J \) is the number of leaf nodes.

Iteration is carried out until the value of the loss function reaches the expected error, and the final fitting result of \( t \) iterations is the sum of the fitting values obtained in each iteration, which is given by the following function.

\[ H(x) = h_0(x) + \sum_{i=1}^{t} \sum_{j=1}^{J} c_{ij}(x \in R_j) \]  

(8)

### 3.1.2 Extreme gradient boosting (XGBoost)

XGBoost is an improvement on the GBDT algorithm [29, 30]. The basic principle of these two algorithms is the same; the difference is the loss function. XGBoost algorithm performs second-order Taylor formula expansion on the loss function, shown in the following function.

\[ r_i = -\frac{\partial L(y, h_{i-1}(x))}{\partial h_{i-1}(x)} - \frac{1}{2} \frac{\partial^2 L(y, h_{i-1}(x))}{\partial h_{i-1}^2(x)} \]  

(9)

In addition, the XGBoost algorithm also adds regular terms, as is given by the following function, in each iteration to reduce the variance of the model and prevent over-fitting of the model.

\[ \Omega(f_t) = \gamma T + \frac{1}{2} \sum_{j=1}^{T} w_j^2 \]  

(10)

where \( T \) is the number of leaf nodes, \( w \) is the weight value of each leaf node, and \( \lambda \) is its coefficient.

### 3.1.3 Light gradient boosting machine (LightGBM)

LightGBM algorithm is improved on the basis of XGBoost and GBDT algorithm [32]. The difference lies in that, in feature selection and leaf node splitting, the LightGBM algorithm adopts a histogram algorithm to scatter continuous floating-point features into \( k \) discrete values and construct a histogram with the width of \( k \). In feature selection, the optimal segmentation point can be found according to the discrete value of the histogram.

### 3.1.4 Categorical boosting (CatBoost)

CatBoost algorithm is also improved on the basis of XGBoost algorithm. In CatBoost algorithm, the step of modifying categorical features to numerical features in the process of establishing a regression model can be eliminated. CatBoost also uses combined category features, which can take advantage of connections between features. It can achieve the advantages of fewer parameters, support for category-based variables, and higher accuracy [33]. Compared with other algorithms, CatBoost has better robustness. The loss function can also be customized. Fewer hyper-parameters can reduce the need for tuning and reduce overfitting.

### 3.2 Parameter setting and model evaluation

#### 3.2.1 Data variables

According to Table 1, the variables of open PHP in this study mainly included heat flux power (\( Q \)), ratio of inner and outer diameter of PHP (\( D_i/D_o \)), length of PHP (\( l \)), working angle (\( \alpha \)), and types of working fluids. The equivalent thermal resistance (\( R_{eff} \)) was selected to evaluate the heat transfer performance, so it was also selected as the output in the prediction model. When selecting the input parameters for the prediction model, \( Q, D_i/D_o, l, \) and \( \alpha \) can be directly selected because they are numerical values. The dimensionless number can be chosen as the input parameter to represent the types of working fluids. Except for \( Ja \) number which requires the temperature of the evaporation section, \( Ku, Bo, Mo, \) and \( Pr \) number can be selected and solved by formulas in literature [4].

In order to prevent redundant input features, correlation analysis was used to study the correlation between the 8 input parameters. Because the data was not completely a normal distribution, Spearman correlation coefficient was used to indicate the strength of the correlation. It can be seen from the specific analysis of Fig. 5 that the combinations of
parameters with a strong correlation higher than 0.5 included $Bo$ and $D_i/D_o$, $Ku$ and $Mo$, and $Pr$ and $Mo$. The combinations with a weak correlation higher than 0.2 included $Ku$ and $Q$, $Ku$ and $Bo$, $Ku$ and $Pr$, $Bo$ and $Mo$, and $Bo$ and $Pr$. Other coefficients had little correlation. Therefore, some dimensionless parameters need to be removed to reduce the number of input variables to reduce the redundancy of the prediction model.

Finally, after screening, the prediction model in this study has five inputs, $Q$, $D_i/D_o$, $L$, $\alpha$, $Pr$ number, and one output, $Re_{eff}$. A total of 432 sets of experimental data were obtained from heat transfer experiments. In the total data set, 85% of the data were selected as the training set and 15% as the verification set. In order to obtain a reliable and stable prediction model, this study adopts the method of fivefold cross-validation. The data set was divided into 5 parts, 4 of which were used as training set and 1 as verification set in turn. Random search method was used to optimize the model hyper-parameters. The resulting optimal hyper-parameters are shown in Table 2.

### 3.2.2 Performance assessment and model training

The prediction model obtained by the final training needs a series of evaluation indexes to evaluate its prediction effect. The evaluation index of this study included root mean square error (RMSE), mean absolute percent error (MAPE), and $R$-squared ($R^2$). RMSE can reflect the deviation between the predicted value and the real value of the regression model. Because the error of each point is normalized, MAPE can reduce the influence of absolute error caused by an outlier point and has better robustness. $R$-squared value is the degree to which the regression model fits the observed value. The closer $R$-squared value is to 1, the better the fitting effect of the regression model is. The framework of the prediction model is shown in Fig. 6.

The performance metrics are calculated as:

\[
RMSE = \sqrt{\frac{\sum_{k=1}^{n} (y_k - \overline{y}_k)^2}{n}} 
\]

\[
MAPE = \frac{\sum_{k=1}^{n} \left| \frac{y_k - \overline{y}_k}{\overline{y}_k} \right| \times 100}{n} 
\]

### Table 2  Tuned hyper-parameters for different models

| Model   | Hyper-parameters   | Optimum values |
|---------|--------------------|----------------|
| GBDT    | learning_rate      | 0.1            |
|         | n_estimators       | 1060           |
|         | max_depth          | 5              |
|         | min_sample_split   | 8              |
| XGBoost | learning_rate      | 0.11           |
|         | max_depth          | 8              |
|         | min_child_weight   | 5              |
|         | n_estimate         | 1060           |
| LightGBM| max_depth          | 8              |
|         | learning_rate      | 0.19           |
|         | min_child_weight   | 2              |
|         | num_iterations     | 360            |
| CatBoost| max_depth          | 8              |
|         | learning_rate      | 0.1            |
|         | l2_leaf-reg        | 2              |
|         | iterations         | 1290           |
where $y_k$ is the actual value of equivalent thermal resistance, $\bar{y}_k$ is the predicted value of equivalent thermal resistance, and $y_{mean}$ is the average value of the actual equivalent thermal resistance. $k$ is the number of independent variables, and $n$ is the number of samples in the validation set.

### 3.2.3 Feature importance and tree structures

Compared with neural network and other models, the integrated algorithm based on decision tree has two better characteristics. The first advantage is that the relative importance of the features used by the model can be output. This allows us to select features and understand which factors are critical to model predictions [31].

Another advantage is that instead of the neural network model as a black box, the integrated learning based on decision tree can realize the visualization of decision tree and facilitate a better understanding of the construction of the prediction model [29, 38]. As is shown in Fig. 7, there are three types of tree structure, depending on how the leaves are divided. Different degrees of color represent different leaf types, and the sum of the weights within the leaf types range constitutes the predicted value. GBDT and XGBoost method use the first leaf division strategy, level-wise, shown in Fig. 7a. Leaves at the same layer are divided by multiple threads, and the weights are mostly different. LightGBM method uses the leaf-wise strategy with depth limits shown in Fig. 7b, which only divides leaves with large weights. This method can reduce unnecessary leaf division and speed up the prediction process. As is shown in Fig. 7c, CatBoost directly uses a symmetric decision tree, in which the two split leaves have the same split types. This strategy can solve the problem of overfitting.

### 4 Results and discussion of heat transfer experiment

#### 4.1 Temperature change analysis for various working fluids

In this study, DI water, ethanol, and 5% Al$_2$O$_3$ nanofluids were selected as the working mediums. Qian et al. [39] proposed an evaluation model to discuss the start-up and operating behaviors of closed PHP based on the second-order dynamic model, including over-damped mode, transient mode, and under-damped mode. In this study, the operating characteristics of open PHPs were consistent with this model. Figures 8, 9, 10, 11, 12, 13 and 14 show the operating temperatures of various working fluids when the heat flux power is about 10 W, 20 W, and 30 W. “DI water(E)” means the temperature of the evaporation section of open PHP with DI water, while “DI Water(C)” means the temperature of the condensation section.

It can be seen from Fig. 8 that the temperature variation trend of the evaporation section of open PHP with three different working mediums conformed to the trend of closed PHP in literature [39]: the rising range decreased gradually and finally stabilized at a certain temperature. The average temperature of evaporation sections of PHP with ethanol and nanofluids finally stabilized at about 58 °C, and that with DI water finally stabilized at 46 °C. DI water had a lower temperature due to its high specific heat capacity and latent heat of vaporization while absorbing the same amount of heat. According to the evaluation model, the start-up mode of PHP in Fig. 8 was similar to the over-damped mode, in which the temperature of the evaporating section of PHP rises steadily without fluctuation. However, the average temperature of evaporation sections of open PHP was about 10 °C higher than that of closed PHP [39] at the same length 150 mm.
Figure 9 shows the visualized operating process of open PHP at 10 W heat flux, which can be used to illustrate the temperature rule in Fig. 8. When the heat flux was loaded for about 100 s, the working medium inside open PHP was heated and gradually began to produce microbubbles. Because the internal pressure of the three channels was not uniform, the size and formation rate of microbubbles in each channel were different. As is shown in Fig. 9, in general, there was a channel of open PHP that generated the most microbubbles which also had the fastest formation rate, and those microbubbles continued to grow into larger bubbles. In Fig. 9a, b, DI water and ethanol microbubbles moved toward the condensation section, while nanofluid bubbles attached to the PHP wall along with Al2O3 particles shown in Fig. 9c. When the heat flux was loaded for 300 s, the evaporation section at the bottom continuously generated growing bubbles, which eventually expanded to form a long vapor plug. In Fig. 9a, b, although large bubbles and vapor plugs were constantly produced in...
DI water and ethanol, they were located in the adiabatic section rather than the evaporation section. The evaporation area where temperature would be collected was still predominantly liquid. Therefore, although there was liquid evaporation inside the open PHP, the temperature trend obtained was still the trend of liquid heated gradually, that is, the temperature rose steadily with time. In Fig. 9c, because nanofluids had the highest boiling point, the formation of bubbles and vapor...
plugs was not the same intense as the other two working mediums. Although the vapor plug was generated, it was basically in a stopped state. Thus, the Al₂O₃ particles in the vapor plug precipitated on the bottom of open PHP due to gravity, which can be seen in the deeper white in Fig. 9c. Then, the particles absorbed heat to increase the total temperature of the evaporation section steadily.

In Fig. 10, under the heating power of 20 W, the evaporation temperature of PHP with ethanol fluctuated between 73 and 84 °C. The evaporation temperature of PHP with DI water fluctuated between 74 and 90 °C. The temperature fluctuation time of PHP with nanofluids was only about 50 s, and the temperature fluctuation range was smaller. This start-up mode of PHP in Fig. 10 conformed to the transient mode in literature [39], in which the temperature of the evaporating section rises rapidly and then fluctuates around a stable temperature range. Figure 11 shows the operating state at 20 W heat flux. The operating states of the three working mediums were similar. In Fig. 11, a red box marked one of the liquid columns, and a white box marked one of the vapor plugs. First, the liquid column and the vapor plug moved down from the right pipeline to the left one. At this time, the evaporation section was mainly the liquid, and the measured temperature was the temperature of the liquid. After that, when the vapor plug moved to the left pipeline, the evaporation section at this time was mainly the vapor, and the measured temperature was the temperature of the vapor, higher than the temperature of the liquid. The vapor plug then moved back to the right side and the evaporation section was again occupied by the liquid. Then, the vapor plug again occupied the evaporation section. These left and right oscillations of the vapor plug were different from the annular flow [7] of the closed PHP and created up and down fluctuations of the measured temperature of the evaporation section in Fig. 10.

Because compared with ethanol, DI water has higher boiling points, and the temperature of the vapor plug formed in DI water was higher than that in ethanol. Thus, the maximum temperature of PHP with DI water was higher than that with ethanol. In addition, the Al₂O₃ nanofluid had the highest boiling point and thus had the longest time to start vapor plug formation at about 100 s.
In Fig. 12, under the heating power of 30 W, the temperature of the evaporation section of PHP with ethanol rose to 135 °C first and then decreased and stabilized at 114 °C. The evaporation temperature of PHP with DI water rose to 140 °C first, then fell to 108 °C, and finally rose steadily. The evaporation temperature of PHP with nanofluids rose to 119 °C first and then decreased and stabilized at 114 °C. It also had smaller temperature fluctuation. The temperature of evaporation sections of open PHP with nanofluids was the lowest at heat flux power of 30 W and the highest at 10 W and 20 W. Figure 13 shows the oscillating motion of DI water at a heat flux of 30 W, while Fig. 14 shows the oscillating motion of nanofluids. DI water and ethanol had similar phenomena when oscillating, both producing large bubbles first, and causing evaporation section in a dry-out state rapidly in Fig. 13, which led to an instant rise in the temperature of the evaporation section to a very high temperature shown in Fig. 12. Then, the backflow was formed by gravity, and liquid drops fell back to the evaporation section, which reduced the temperature of the evaporation section. Finally, a steady process of liquid drops, falling back to the evaporation section and then rising to the condensation section, was gradually formed in the PHP, which led to the temperature trend in Fig. 12. This research conclusion was similar to the results in the literature [39] in which there were dry-out and backflow phenomena when the heat flux was high. This start-up mode of PHP conformed to the under-damped mode in which the temperature of the evaporating section rises rapidly, then drops sharply, and quickly reaches a stable state.

In Fig. 14, in addition to dry-out and backflow, broken bubbles also existed in the nanofluids. Due to the presence of Al2O3 particles in the bubble, the bubbles were broken due to gravity during the ascent to the condensation section and the particles were dissipated. This process made the Al2O3 particles move up and down in the PHP. This phenomenon was the same as in literature [7] that at high heat flux power,
nanofluids oscillated in PHP and transferred more heat than DI water and ethanol while entering a transient boiling regime. Therefore, the open PHP with nanofluids as working medium had the lowest operating temperature in Fig. 12.

In terms of closed PHP, the three operating modes corresponded to different working fluid motion states, production of few bubbles, stable oscillations, and vigorous liquid–vapor circulation. In general, compared with the closed PHP, the open PHP had almost the same operating characteristics under different heat flux power. In addition, the heat transfer performance of open PHP with DI water as the working fluid was the best at low heat flux power, while the heat transfer performance of nanofluids was the best at high heat flux power. The difference between the closed PHP and the open PHP was that the oscillation mode was left and right flow instead of annular flow due to the structure. In addition, compared with literature [39], the operating temperature of the open PHP was about 10 ~ 40 °C higher.

4.2 Thermal resistance analysis for various variables

When analyzing the effect of other variables on the $R_{\text{eff}}$ of PHP, it is only necessary to select one of the working fluids because of the similar operating characteristic. DI water was used in this study due to its more widespread use. Four variables, $Q$, $D/D_o$, $L$, and $\alpha$, were used to analyze the $R_{\text{eff}}$. Figure 15 shows the $R_{\text{eff}}$ of open PHPs with $L$ of 150 mm and other different parameters. Figures 15a and 16 show the $R_{\text{eff}}$ with $D/D_o$ of 0.5 and different other parameters. Figures 15d and 17 show the $R_{\text{eff}}$ with $D/D_o$ of 0.6667 and other different parameters.

Firstly, it can be concluded from Fig. 15 that when other parameters were constant, the $R_{\text{eff}}$ of PHPs decreased gradually with the increase of $D/D_o$. This result was consistent with that in literature [7]. For example, when the heat flux power was 10 W and the working angle was 90°, the $R_{\text{eff}}$ decreased from 1.27 °C/W with $D/D_o$ of 0.5 to 1.01 °C/W with $D/D_o$ of 0.545, then to 1.00 °C/W of 0.6, and finally to 0.51 °C/W of 0.667. When the power was 30 W and the working angle was 60°, the $R_{\text{eff}}$ decreased from 1.24 °C/W with $D/D_o$ of 0.5 to 1.07 °C/W of 0.545, then to 0.96 °C/W of 0.6, and finally decrease to 0.90 °C/W of 0.667. In fact, as is shown in Fig. 15b, c, the $R_{\text{eff}}$ of the two kinds of PHPs with $D/D_o$ of 0.545 and 0.6 was similar, so they can be regarded as PHPs with similar performance for subsequent research. When the $D/D_o$ was 0.5, the range of $R_{\text{eff}}$ was the largest, ranging from 1.12 to 1.85 °C/W. The $R_{\text{eff}}$ ranges of the PHPs with $D/D_o$ of 0.545 and 0.6 were about 0.98 ~ 1.41 °C/W. The $R_{\text{eff}}$ range of the PHPs with $D/D_o$ of 0.667 was the smallest, ranging from 0.51 to 1.00 °C/W. As explained in literature [7], with the smaller the inner diameter, the working fluid in the heat pipe tube encountered the greater resistance of oscillation. The smaller diameter also had a positive effect on the backflow of the working fluid to the

Fig. 15 Comparison of $R_{\text{eff}}$ of PHP with $L$ of 150 mm with different $D/D_o$. a 0.5. b 0.545. c 0.6. d 0.667
evaporation section. Secondly, the influence of different $Q$ and $\alpha$ on the $R_{\text{eff}}$ when $L$ was 150 mm can be obtained from each figure in Fig. 15. It can be obviously obtained that when $D_i/D_o$ was 0.5, 0.545, and 0.6, the $R_{\text{eff}}$ decreased gradually with the increase of heat flux power. The reason was that the heat transfer phenomenon was more intense resulting in the improvement of the heat transfer effect. This result was consistent with the experimental results in literature [18, 20]. However, when $D_i/D_o$ was 0.6, there was an opposite trend that the $R_{\text{eff}}$ increased with the increase of $Q$. In other words, when the $D_i/D_o$ continued to increase, the $R_{\text{eff}}$ of PHPs with lower $Q$ decreased faster, resulting in lower $R_{\text{eff}}$ with lower $Q$. Finally, when the $Q$ and $D_i/D_o$ were constant, the $R_{\text{eff}}$ of open PHPs decreased with the increase of $\alpha$, but the downward trend was not uniform. In general, the $R_{\text{eff}}$ of open PHPs with larger inclination angles, 60° and 90°, was lower than that of 0° and 30°, which was consistent with the experimental results in literature [18].

According to the comparison between Figs. 15a and 16, when the $D_i/D_o$ was 0.5, the $R_{\text{eff}}$ of the PHPs decreased with increasing $L$, except when the $L$ was 200 mm and the $\alpha$ was 90°. The range of $R_{\text{eff}}$ dropped from 1.73~3.15 °C/W with $L$ of 100 mm to 1.12~1.85 °C/W with $L$ of 150 mm and finally to 0.84~1.31 °C/W with $L$ of 200 mm. When the $D_i/D_o$ was 0.545 and 0.6, the influence trend on $R_{\text{eff}}$ was almost the same. The comparison between Figs. 15d and 17 shows that contrary to that trend, when the $D_i/D_o$ was 3 mm, the $R_{\text{eff}}$ of the PHPs increased with increasing $L$, and the variation range was smaller. The range of $R_{\text{eff}}$ dropped from 0.99~1.60 °C/W with $L$ of 100 mm to 0.51~1.00 °C/W with $L$ of 150 mm and finally to 0.52~0.76 °C/W with $L$ of 200 mm. In addition, the $R_{\text{eff}}$ decreased with the increase of $\alpha$ and $Q$.

In general, the $R_{\text{eff}}$ decreased with the increase of the $D_i/D_o$ and $L$ of PHP. The PHP with better performance can be obtained by choosing higher $\alpha$, $D_i/D_o$, and $L$. In most cases, $R_{\text{eff}}$ decreased gradually with the increase of $Q$, but the trend was the opposite when the $D_i/D_o$ is large. Therefore, in the actual selection, the PHP with the best heat transfer performance can be selected according to the heat transfer law after the working fluids and parameter range are determined. However, several PHPs with different parameters or working fluids need to be compared in the actual machining process. For example, when comparing the PHP with larger $D_i/D_o$ and smaller $L$ with those with smaller $D_i/D_o$ and larger $L$, it is impossible to directly select the one with the best performance through heat transfer law. Therefore, it is necessary to establish a prediction model of the $R_{\text{eff}}$ of PHPs, and this difficulty can be overcome by this method.

### 5 Results and discussion of the prediction model

#### 5.1 Prediction results

Based on the same training set and validation set, the goodness-of-fit of the four models was adjusted to be the same as possible. In terms of RMSE, MAPE, $R^2$, and run time metrics, the results in Table 3 show the goodness-of-fit and predictive performance of these four models. It can be concluded that the CatBoost model optimized by hyper-parameters had the similar best goodness of fit with the XGBoost model, but had the best prediction performance when using the data of this study to build the model. From the results of the training data set, the four prediction models by hyper-parameters optimized all had a good fitting performance. The RMSE of the four models were all lower than 0.1 while the $R^2$ values of those were higher than 0.92. XGBoost model had the best fitting performance with $R^2$ value of 0.9996, MAPE value of 0.3704, and RMSE value of 0.0068, followed by the GBDT model with $R^2$ value of 0.9996, MAPE value of 0.3818, and RMSE value of 0.0070. The goodness-of-fit of the CatBoost model was close to these two models. In terms of prediction results of the validation data set, the CatBoost model had the highest prediction performance with the $R^2$ value of 0.9258, MAPE value of 7.2564, and RMSE value of 0.1057, followed...
by the XGBoost model with the $R^2$ value of 0.9004, MAPE value of 8.6285, and RMSE value of 0.1225. However, with a similar goodness-of-fit performance, the prediction effect of the CatBoost model was much higher than the XGBoost model. However, the CatBoost model had the disadvantage of a much longer run time, 4.48 s, than other models. In contrast, although the LightGBM model with leaf-wise strategy had the lowest fitting and predictive performance and the largest MAPE value, it had the shortest run time. As a result, the CatBoost model was the best in this study in terms of goodness-of-fit and predictive performance, but run time needs to be taken into account when predicting large amounts of data. The results of the prediction model were similar to those in literature [29] but worse than those in literature [4, 25, 26]. However, given the larger amount of data in this study, the results of the prediction model obtained were acceptable.

Figure 18 shows the linear relationship between actual measured values and predicted values of the four models. As can be seen from the figures, the relationship between the predicted value and the actual measured value was almost linear. The linear fitting curve and equation of the test data set were also shown in Fig. 18. By comparing the slope and intercept of the curve, it can be seen that the fitting curve of the CatBoost model was the closest to the line “$Y=X$”, indicating that the prediction result was the closest to the actual experimental value. Figure 19 shows the relative errors of prediction for total data. In terms of the training set, except for the LightGBM model in Fig. 19c, most of the relative errors of data were within 10%. In terms of the validation set, most of the relative errors of data were within 20%. Each model had a few predicted values with errors larger than 20%.

Figure 20 shows the percentages for the different error ranges. As can be seen from the figure, the percentage of errors of the four models less than 10% was 58.46%, 70.77%, 83.07%, and 86.16% respectively. The percentages with an error range larger than 20% are 7.69%, 7.69%, 7.69%, and 4.62%, respectively. By comparing the errors of the four models, it can be concluded that the CatBoost model has the best prediction performance, the highest proportion in the range of less than 5% and 10%, and the lowest proportion in the range of more than 20%. However, when comparing all values with large error from each figure in Fig. 19, it can be concluded that they were almost the same data with the same parameters, such as the experimental data with $R_{\text{eff}}$ of 0.7796, 0.8395, and 0.8850. That means it was not necessarily a problem with the model, but an error caused by the accident of the data acquisition process. These values with large errors in the four models can be re-tested by the same experiment in order to increase the accuracy of the prediction model.

### 5.2 The guidance provided for the experiment by the prediction model

The prediction model is closely related to the experimental part. First of all, the result of the prediction model

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**Table 3** RMSE, MAPE, $R^2$, and run time for different models

| Method    | Training set | Validation set |
|-----------|--------------|----------------|
|           | RMSE | MAPE | $R^2$ | RMSE | MAPE | $R^2$ | Run time (s) |
| GBDT      | 0.0070 | 0.3818 | 0.9996 | 0.1351 | 9.2173 | 0.8787 | 0.4922 |
| XGBoost   | 0.0068 | 0.3704 | 0.9996 | 0.1225 | 8.6285 | 0.9004 | 1.7851 |
| LightGBM  | 0.0970 | 6.2290 | 0.9283 | 0.1289 | 8.7799 | 0.8897 | 0.1478 |
| CatBoost  | 0.0071 | 0.3863 | 0.9996 | 0.1057 | 7.2564 | 0.9258 | 4.6116 |
can guide the original experiment. Compared with neural networks, these four machine learning methods selected in this study can obtain the importance of each input feature to predict the output and the decision tree structure which can show the prediction process. Figure 21 shows the order of importance of the five features to the predicted output in the CatBoost model. As can be seen from the figure, the top three variables with a strong influence on the prediction results are $L$, $D_i/D_o$, and $Pr$, respectively. When the subsequent experiments need further improvement, the variation range of parameter coefficients can be determined according to the importance of parameters in the prediction model. This process not only facilitates the selection of variables that need to be changed in subsequent experiments but also has guiding significance for the results of decision trees. In this study, a total of 1290
sub-cart trees were constructed to construct the CatBoost model. Since the sub-cart tree in the CatBoost model had the same type of leaf in the same layer, only a portion of each tree was taken. As is shown in Fig. 22, in order to better illustrate the basis of prediction, 4 typical trees were selected sequentially to display the structures, with the tree index \{0, 1, 10, and 100\}, respectively. The value at the bottom was the weight of the tree structure. The final prediction result was the sum of the weights of trees within the range of tree parameters. The first few trees of the decision tree try to improve the predicted results as much as possible to an acceptable range according to the contributions of features. The order of tree index represents the importance of the model for prediction, and the trees at the top of the order have more weight. As is shown in Fig. 22a–c, corresponding to the ranking of feature importance, \(L\) had the highest frequency of occurrence and more weight. Then, in Fig. 22d, \(Q\), with the least importance, was used to build subsequent trees and was given tiny weights compared with \(L\) as is shown in Fig. 22a–c. There was also a branch of the tree with the weight of 0, which means that this branch had no effect on the predicted results. Thus, it can be concluded that the high weight of the first few trees is an important part of the prediction result.

Secondly, the predicted results can guide the summary of the experimental rule. In this study, when the coefficient of experimental parameters was the median, the prediction
effect was the best, and the error was mostly less than 5%, for example, when the length was 150 mm, the ratio of inner and outer diameter ratio was 0.6, and the heat flux power was 20 W. This means that the open PHPs had more obvious running rules under these conditions. By studying the law of these predicted results, the similar law of experimental data can be obtained. The data with poor prediction effect may be caused by unclear rules or experimental errors, so the correctness of this value can be verified through multiple experiments.

Thirdly, this prediction model can be used to select the best open PHP in the research of self-cooling cutting tools. Among the five input variables of the prediction model in this study, except for the heat flux $Q$, other variables are easy to obtain directly. It is necessary to study how to obtain the heat flux $Q$ roughly equal to the heat transferred by the open PHP in the actual cutting process. In the previous research [5, 6], the tool tip temperature and the temperature field distribution of the cutting tool in the actual cutting process were obtained by means of the finite element simulation method (FEM). The heat flux inverse procedure was used to establish the cutting model by the temperature data. The error between simulated temperature result and actual measurement result was regarded as the optimization problem of the optimization objective function. The value of heat flux which meets the precision requirement on the chip contact surface was obtained. This value was approximately close to the heat flux of cutting heat into the tool. Liang and Quan [40] proposed a method to calculate the proportion of heat transferred by gravity-assisted heat pipe in the cutting process. The heat dissipated by heat accounting for 0.36 ~ 0.42 of the cutting heat into the cutting tool was finally obtained. Therefore, based on the temperature measurement data of the subsequent cutting experiment, the proportion of the heat transferred by open PHP can be obtained by using this method. The proportion is multiplied by the inverse value of the heat flux of the cutting tool, and the approximate transferred heat flux by open PHP in cutting process can be obtained. This numerical value is applied to
In the present research of PHP, there are also a series of parameters such as wall material, section shape, and the number of turns. Existing input variables can also be added with more variable values. These need to obtain more experimental data through subsequent experiments and be added to the training set to improve the training parameters of the model.

6 Conclusions

An experimental investigation, as well as a machine learning prediction model, of the heat transfer performance of open pulsating heat pipe was conducted. The effect of five variables, namely heat flux power \(Q\), length \(L\), ratio of inner and outer diameter \(D_i/D_o\), inclination angle \(\alpha\), and working medium, on the equivalent thermal resistance \(R_{\text{eff}}\) of open pulsating heat pipe was studied. Four boosting integrated learning methods, namely GBDT, XGBoost, LightGBM, and CatBoost, were used to establish the prediction model for heat transfer performance. The main conclusions are drawn as follows:

1. The operating characteristics of the three working fluids, namely DI water, ethanol, and Al\(_2\)O\(_3\) nano- fluids, in the open PHP were consistent with those in the closed PHP. The difference between the open PHP and the closed PHP was that the oscillation mode
was left and right rather than circular flow. At $Q$ of 10 W, the evaporation temperature gradually rose and became stable. DI water had the best heat transfer effect. Under the $Q$ of 20 W, the evaporation temperature rose first and then oscillated within a certain temperature range. At $Q$ of 30 W, the evaporation temperature rose sharply first, then decreased, and finally became stable. The nanofluid had the best heat transfer effect.

2. The $R_{\text{eff}}$ of the open PHP decreased with the increase of $D/D_o$. The $R_{\text{eff}}$ was similar when $D/D_o$ was 0.545 and 0.6. In most cases, $R_{\text{eff}}$ gradually decreased with the increase of $Q$, but when $D/D_o$ was large, the trend was the opposite. The $R_{\text{eff}}$ also decreased with the increase of $L$ and $a$.

3. By comparing the performance of the prediction models established by four methods, it can be concluded that the XGBoost model had the best goodness-of-fit effect based on the training set. The CatBoost model had the best prediction performance. The LightGBM model had the shortest run time. In general, CatBoost was the best method for the prediction model in this study. On the one hand, this prediction model can provide the influence degree of each parameters on the heat transfer performance of PHP and provide guidance for the subsequent improvement of experimental parameters. On the other hand, this model can select the PHP with the best performance, which can be applied to the research of PHP cooling tool.

**Author contribution** Ze Wu: Conceptualization, investigation, writing original draft. Hang Bao: Formal analysis, supervision, writing code. Youqiang Xing: Formal analysis, supervision. Lei Liu: Project administration.

**Funding** This work was supported by the National Natural Science Foundation of China (Grant no. 52075097), Natural Science Foundation of Jiangsu Province in China (Grant no. BK20211562), and Zhishan Young Scholar Foundation of Southeast University in China (Grant no.2242021R41147).

**Availability of data and material** Not applicable.

**Declarations**

**Ethics approval** The work contains no libelous or unlawful statements, does not infringe on the rights of others, or contains material or instructions that might cause harm or injury.

**Consent to participate** The authors declared their approval to participate in the submitted manuscript.

**Consent for publication** All authors have given their permission for publishing this work.

**Competing interests** The authors declare no competing interests.

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