Research Article

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Thermal-hydraulic performance prediction of two new heat exchangers using RBF based on different DOE

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Abstract: Thermal performance prediction with high precision and low cost is always the need for designers of heat exchangers. Three typical design of experiments (DOE) known as Taguchi design method (TDM), Uniform design method (UDM), and Response surface method (RSM) are commonly used to reduce experimental cost. The radial basis function artificial neural network (RBF) based on different DOE is used to predict the thermal performance of two new parallel-flow shell and tube heat exchangers. The applicability and expense of ten different prediction methods (RBF + TDML9, RBF + TDML18, RBF + UDM, RBF + TDML9 + UDM, RBF + TDML18 + UDM, RBF + RSM, RBF + RSM + TDML9, RBF + RSM + TDML18, RBF + RSM + UDM, RSM) are discussed. The results show that the RBF + RSM is a very efficient method for the precise prediction of thermal-hydraulic performance: the minimum error is 2.17% for Nu and 5.30% for f . For RBF, it is not true that the more of train data, the more precision of the prediction. The parameter “spread” of RBF should be adjusted to optimize the prediction results. The prediction using RSM only can also obtain a good balance between precision and time cost with a maximum prediction error of 14.52%.

Keywords: heat exchanger, thermal-hydraulic performance, prediction, RBF, design of experiments

Nomenclature

A	area, mm ²
A_{in}	area of cross-section (mm ²)
a	length (mm)
b	baffle width (mm)
c	length (mm)
C_p	specific heat at constant pressure (J kg ⁻¹ K ⁻¹)
d_c	coil diameter (mm)
d_i	inner diameter of tube (mm)
d_o	outer diameter of tube (mm)
d_r	diameter of rod (mm)
D_h	hydraulic diameter (mm)
f	average friction factor (–)
h	convection heat transfer coefficient (W m ² K ⁻¹)
L	length (mm)
L_b	baffle distance (mm)
l_{et}	length of equilateral triangular section (mm)
P_c	coil pitch (mm)
p	pressure (Pa)
P_t	tube pitch (mm)
ΔT	log-mean temperature difference (K)
T	temperature (K)
T_a	tape amplitude (mm)
T_w	tape width (mm)
T_t	tape thickness (mm)
T_p	tape pitch (mm)
t	thickness (mm)
u	velocity (m s ⁻¹)
V_{in}	inlet velocity (m s ⁻¹)
t_b	baffle thickness (mm)
Re	Reynolds number (–)
R	radius (mm)
Pr	Prandtl number (–)
Δp	pressure drop (Pa)

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Greek symbols

ρ	density (kg m^{-3})
ε	turbulence kinetic energy dissipation rate
k	turbulence kinetic energy
μ	dynamic viscosity ($\text{kg m}^{-1} \text{s}^{-1}$)
λ	thermal conductivity ($\text{W m}^{-1} \text{K}^{-1}$)

Subscripts

w	wall
in	inlet
out	outlet
rod	round rod
RRB	RRB-STHX
ETWC	STHX-CPBETWC
SWT	STHX-CPBSWT

Abbreviations

ANN	artificial neural network
ANOVA	analysis of variance
CCD	central composite design
CPB	clamping plate baffle
CFD	numerical result obtained by computation
	fluid mechanics
DOE	design of experiments
Pre	prediction result
RBF	radial basis function artificial neural network
RRB	round rod baffle
RSM	response surface methodology
SWT	sinusoidal wavy tape
STHX	shell and tube heat exchanger
TDM	Taguchi method
MLFF	multilayer feed forward artificial neural network
UDM	uniform design method

1 Introduction

Shell and tube heat exchangers (STHXs) are widely used in various industries [1]. The greatest advantage of the STHXs over other types of heat exchangers is that they can withstand very high temperature and pressure simultaneously at a low cost [2]. As a result, it can be found

that the STHXs are almost the only candidate for high pressure feed water heaters in thermal power plants [3].

As a whole, the STHXs can be classified into three basic types according to the fluid flow path: cross flow, parallel flow, and helical flow [4]. Among the three types, the parallel-flow STHXs are more promising because they have the merits of both helical flow STHXs (low fouling and pressure drop, etc.) and cross flow STHXs (high heat transfer rate and low cost, etc.). In the past few decades, different parallel-flow STHXs have been proposed [5]. The famous one needed to mention is round rod baffle STHX (RRB-STHX) which is invented by Philips Company to solve the high pressure drop problem of segmental baffle STHX [6]. However, the RRB-STHX is vulnerable to flow-induced vibration failure due to the fact that the round rod and the tube are in point contact status [7]. Very large contact stress occurs when the flow impacts the tube. For this reason, clamping plate baffle (CPB) is proposed. Figure 1 illustrates one example of application of CPB in the 4th generation sodium cooled nuclear power station [8].

In order to save energy and reduce cost, heat transfer enhancement technologies are always the hot point of energy utilization. Two new parallel-flow STHXs with CPB and inserts (STHX-CPBETWC and STHX-CPBSWT) are proposed by Yu *et al.* [9]. The effects of geometrical parameters such as coil pitch, coil diameter, side length of equilateral cross-section, tape amplitude, tape pitch,

Figure 1: Picture of heat exchanger used in the 4th generation sodium cooled nuclear power station.

and tape width on the thermal-hydraulic performance are numerically explored with flow in turbulent regime.

For designers of STHX, it is meaningful to obtain the thermal-hydraulic performance using design of experiments (DOE) to save time and costs. Taguchi design method (TDM), uniform design method (UDM), and response surface method (RSM) are three widely used DOE. TDM developed by Genichi Taguchi is a statistical technique [10]. It can help researchers to learn the effect of many factors on object function with a small cost [11,12]. The uniform experimental design method (UDM) was proposed by Fang and Wang based on the quasi-Monte Carlo method, number theoretic method, and multivariate statistics [13]. Compared with the conventional statistical experimental design methods, the UDM can significantly reduce the number of experiments under the same number of factors and levels [14,15]. The RSM is an empirical modeling approach for determining the relationship between input parameters and responses with the various desired criteria [16]. One of the advantages of the RSM over the conventional experimental methods, in addition to reducing the experimental cost, is that it minimizes the variability around the target [17–19].

Artificial neural network (ANN) is finding increasing use as predictive tool in an extensive range of disciplines due to their strong adaptivity for solving complex and nonlinear systems [20]. Therefore, it has been applied to complex nonlinear engineering problems in different real-world applications with a significant reduction in cost and time. Different types of ANN are used to predict the thermal-hydraulic performance of STHXs [21]. It was reported that the multilayer feed forward artificial networks (MLFF) were the most widely used ANN for heat exchanger analysis due to their simplicity. However, the MLFF has some limitations in optimizing the network parameters [22]. Instead, radial basis function artificial neural network (RBF) has faster convergence, smaller extrapolation errors, and higher reliability than MLFF [23]. Radial Basis Function (RBF) neural network is a very important ANN. It is composed of three main categories of layers (input layer, some hidden layers, and output layer). The input layer in the RBF receives the input data without computing power and passes it through the hidden layer. The hidden layer performs some operations of the received data and extracted relevant information and sends them to the output layer [24]. Elsheikh et al. illustrated merits and debits of RBF [25]. Ghasemi et al. used RBF to predict and optimize energetic efficiency of $\text{TiO}_2\text{-Al}_2\text{O}_3/\text{water}$ nanofluid in mini double pipe heat exchanger [26]. The combination use of ANN and DOE can be found in some references [27–30]. In

most cases, the DOE was used to establish an appropriate structure of ANN. However, to the best of authors' knowledge, the research on the train data design of ANN using DOE is rare. One may wonder if RBF and DOE can be used simultaneously to get a balance between precision and time cost.

Generally, the working flow chart of establishing RBF based on different experimental design methods to predict the thermal performance of STHX is shown in Figure 2. For STHX with the same parameters, the number of experiments needed to obtain the thermal-hydraulic performance numerically is quite different. As a result, the time needed to finish numerical calculation is also quite different. For example, for STHX with four design parameters (each with three levels), a minimum of 9, 10, and 25 experiments are needed according to TDM, UDM, and RSM. In present study, the STHX-CPBETWC and STHX-CPBSWT are taken as two objectives; the applicability and cost of prediction method using RBF based on TDM, UDM, and RSM are learned and discussed.

2 Geometrical structure

For parallel-flow STHX, the sketch of the tube bundle is illustrated in Figure 3. The sketches of ETWC and SWT are shown in Figure 4. The heat exchange tube inside the heat exchanger is arranged in a square form. When the medium flows, turbulence can be formed, which is favorable to the heat transfer process. The tube spacing of the

Figure 2: Working flow chart of prediction of thermal-hydraulic performance of STHX using RBF.

Figure 3: Sketch of tube bundle with CPB.

heat exchange tube is P_t , and the outer diameter of the heat exchange tube is d_o . The clamping plate is used to fix the tubes. The insert element such as ETWC and SWT are placed in the space of the tubes to further enhance the heat transfer.

3 RBF

The construction of RBF involves three layers such as input layer, hidden layer, and output layer, which can be seen from Figure 5. The activation function used in hidden layer is RBF. In the software Matlab [31], two different kinds of RBF are presented (approximate RBF and exact RBF). In this paper, the exact RBF is selected as only one parameter “spread” can affect the precision

Figure 5: Architecture of RBF of STHX-CPBETWC and STHX-CPBSWT.

and convergence of the prediction results. Four design parameters, named P_c , Re , l_{et} , and d_c , are used in the input layer for STHX-CPBETWC, while T_p , Re , T_a , and T_w are used in the input layer for STHX-CPBSWT. In the output layer, the Nu and f are used as the response parameters.

The train of ANN is very crucial. It is well-known that the more of train data, the higher of prediction precision. However, it is not practical to use a full factor test to train the ANN. Furthermore, there is not a well-established principle to decide how to train the ANN [14]. The basic method is trial and error. In this paper, three different experimental methods are used to generate the train data. Table 1 gives a detailed 9 training scheme of RBF. For example, for building method 1 and 2, the train data are generated by the TDML9 and TDML18, respectively. To test the performance of the trained RBF, the test data are generated by the TDM, UDM, and RSM. Two indicators, named the maximum absolute error and sum absolute error of the test data, are adopted. In addition, another prediction method using RSM only is also calcu-

Figure 4: Sketch of two different inserts between tubes. (a) SWT, and (b) ETWC.

Table 1: Different building methods of RBF based on different experimental design methods

Data	Building methods of RBF								
	1	2	3	4	5	6	7	8	9
Train data	TDML9	TDML18	UDM	TDML9 + UDM	TDML18 + UDM	RSM	RSM + TDML9	RSM + TDML18	RSM + UDM
Test data	TDML18 + UDM + RSM								

lated and compared. It is worth noting that L9 is a part of L18 according to the orthogonal array of TDM. So, the test data of RBF is TDML18 + UDM + RSM.

4 Experimental design method

4.1 TDM

TDM is also known as the orthogonal experimental method. Orthogonal experimental design is the study of multiple factors level and a design method. According to orthogonality from the selected part of the comprehensive experiment typical test points, the representative points with the “evenly dispersed, neat comparable to the characteristics of the Orthogonal DOE is the main method of fractional factorial design. It is an efficient, rapid, and economical experimental design method.

According to the theory of TDM, for STHX-ETWC and STHX-SWT, three levels of each factor are chosen as shown in Tables 2 and 3, respectively. Two different orthogonal arrays (L9 and L18) can be used to arrange experiments. The detailed arrangement is shown in Tables 4–7. The value in the bracket represents the actual value of selected factors. The other geometric parameters are the same with those listed in Table 8.

4.2 UDM

According to the theory of UDM, for 4 factors and 10 levels of each factor, the array of experiments is shown

Table 2: The three levels of the selected factors used in TDM for STHX-CPBETWC

Code	Factors (unit)	Level 1	Level 2	Level 3
A	P_c (mm)	20	30	40
B	Re	14,465	21,698	28,931
C	l_{et} (mm)	2	3	4
D	d_c (mm)	13	14	15

in Tables 9 and 10. For the problem discussed in this paper, 5 levels of each factor are used. The quasi-level arrangement is adopted. The basic principle is shown in Figure 6. It illustrates that the level 6 should be substituted with level 1, the level 7 should be substituted with level 2, etc. when only 5 levels of each factor are considered.

4.3 RSM

The RSM is an empirical modeling approach for determining the relationship between input parameters and responses with the various desired criteria. In this study, central composite design of RSM is used to arrange experiments. The factors and levels used in RSM are listed in Tables 11 and 12. The arrangement of experiments is shown in Tables 17 and 21.

It is worth nothing that the RSM can also predict the results by building response surface model. In this paper, the quadratic polynomial model is used to build the response surface model of Nu and f . It can be expressed as follows:

$$Y = b_0 + \sum_{I=1}^N (b_I X_I) + \sum_{I=1}^{N-1} \sum_{J=I+1}^N b_{I,J} X_I X_J + \sum_{I=1}^N (b_{I,I} X_I^2) + \Delta \quad (1)$$

where Y is a response variable; X_I and X_J are the factors or variables; the symbols b_0 , b_I , $b_{I,J}$, and $b_{I,I}$ are constants; N is the number of the factors or variables; Δ is the statistical error.

Table 3: The three levels of the selected factors used in TDM for STHX-CPBSWT

Code	Factors (unit)	Level 1	Level 2	Level 3
A	T_p (mm)	20	30	40
B	Re	14,465	21,698	28,931
C	T_a (mm)	2	4	6
D	T_w (mm)	10	12	14

Table 4: The orthogonal array of experiments of L9 for STHX-CPBETWC

Case no.	Control factors			
	A	B	C	D
1	1 (20)	1 (14,465)	1 (2)	1 (13)
2	1 (20)	2 (21,698)	2 (3)	2 (14)
3	1 (20)	3 (28,931)	3 (4)	3 (15)
4	2 (30)	1 (14,465)	2 (3)	3 (15)
5	2 (30)	2 (21,698)	3 (4)	1 (13)
6	2 (30)	3 (28,931)	1 (2)	2 (14)
7	3 (40)	1 (14,465)	3 (4)	2 (14)
8	3 (40)	2 (21,698)	1 (2)	3 (15)
9	3 (40)	3 (28,931)	2 (3)	1 (13)

Table 5: The orthogonal array of experiments of L18 for STHX-CPBETWC

Case no.	Control factors			
	A	B	C	D
1	1 (20)	1 (14,465)	1 (2)	1 (13)
2	1 (20)	2 (21,698)	2 (3)	2 (14)
3	1 (20)	3 (28,931)	3 (4)	3 (15)
4	2 (30)	1 (14,465)	1 (2)	2 (14)
5	2 (30)	2 (21,698)	2 (3)	3 (15)
6	2 (30)	3 (28,931)	3 (4)	1 (13)
7	3 (40)	1 (14,465)	2 (3)	1 (13)
8	3 (40)	2 (21,698)	3 (4)	2 (14)
9	3 (40)	3 (28,931)	1 (2)	3 (15)
10	1 (20)	1 (14,465)	3 (4)	3 (15)
11	1 (20)	2 (21,698)	1 (2)	1 (13)
12	1 (20)	3 (28,931)	2 (3)	2 (14)
13	2 (30)	1 (14,465)	2 (3)	3 (15)
14	2 (30)	2 (21,698)	3 (4)	1 (13)
15	2 (30)	3 (28,931)	1 (2)	2 (14)
16	3 (40)	1 (14,465)	3 (4)	2 (14)
17	3 (40)	2 (21,698)	1 (2)	3 (15)
18	3 (40)	3 (28,931)	2 (3)	1 (13)

Table 6: The orthogonal array of experiments of L9 for STHX-CPBSWT

Case no.	Control factors			
	A	B	C	D
1	1 (20)	1 (14,465)	1 (2)	1 (10)
2	1 (20)	2 (21,698)	2 (4)	2 (12)
3	1 (20)	3 (28,931)	3 (6)	3 (14)
4	2 (30)	1 (14,465)	2 (4)	3 (14)
5	2 (30)	2 (21,698)	3 (6)	1 (10)
6	2 (30)	3 (28,931)	1 (2)	2 (12)
7	3 (40)	1 (14,465)	3 (6)	2 (12)
8	3 (40)	2 (21,698)	1 (2)	3 (14)
9	3 (40)	3 (28,931)	2 (4)	1 (10)

Table 7: The orthogonal array of experiments of L18 for STHX-CPBSWT

Case no.	Control factors			
	A	B	C	D
1	1 (20)	1 (14,465)	1 (2)	1 (10)
2	1 (20)	2 (21,698)	2 (4)	2 (12)
3	1 (20)	3 (28,931)	3 (6)	3 (14)
4	2 (30)	1 (14,465)	1 (2)	2 (12)
5	2 (30)	2 (21,698)	2 (4)	3 (14)
6	2 (30)	3 (28,931)	3 (6)	1 (10)
7	3 (40)	1 (14,465)	2 (4)	1 (10)
8	3 (40)	2 (21,698)	3 (6)	2 (12)
9	3 (40)	3 (28,931)	1 (2)	3 (14)
10	1 (20)	1 (14,465)	3 (6)	3 (14)
11	1 (20)	2 (21,698)	1 (2)	1 (10)
12	1 (20)	3 (28,931)	2 (4)	2 (12)
13	2 (30)	1 (14,465)	2 (4)	3 (14)
14	2 (30)	2 (21,698)	3 (6)	1 (10)
15	2 (30)	3 (28,931)	1 (2)	2 (12)
16	3 (40)	1 (14,465)	3 (6)	2 (12)
17	3 (40)	2 (21,698)	1 (2)	3 (14)
18	3 (40)	3 (28,931)	2 (4)	1 (10)

Table 8: The other geometric parameters of STHX-CPBETWC and STHX-CPBSWT

Parameter	d_o	P_t	d_r	L_b	a	b	c	tb
Value	25	32	6	400	10	20	10	3

Table 9: The array of experiments of U11¹⁰ for STHX-CPBETWC

Case no.	Control factors			
	A	B	C	D
1	1 (20)	2 (18,082)	5 (4)	7 (13.5)
2	2 (25)	4 (25,315)	10 (4)	3 (14)
3	3 (30)	6 (14,465)	4 (3.5)	10 (15)
4	4 (35)	8 (21,698)	9 (3.5)	6 (13)
5	5 (40)	10 (28,931)	3 (3)	2 (13.5)
6	6 (20)	1 (14,465)	8 (3)	9 (14.5)
7	7 (25)	3 (21,698)	2 (2.5)	5 (15)
8	8 (30)	5 (28,931)	7 (2.5)	1 (13)
9	9 (35)	7 (18,082)	1 (2)	8 (14)
10	10 (40)	9 (25,315)	6 (2)	4 (14.5)

5 Numerical model

5.1 Computational domain

The computational domain and mesh scheme of the STHX-CPBETWC and STHX-CPBSWT are shown in

Table 10: The array of experiments of U11¹⁰ for STHX-CPBSWT

Case no.	Control factors			
	A	B	C	D
1	1 (20)	2 (18,082)	5 (6)	7 (11)
2	2 (25)	4 (25,315)	10 (6)	3 (12)
3	3 (30)	6 (14,465)	4 (5)	10 (14)
4	4 (35)	8 (21,698)	9 (5)	6 (10)
5	5 (40)	10 (28,931)	3 (4)	2 (11)
6	6 (20)	1 (14,465)	8 (4)	9 (13)
7	7 (25)	3 (21,698)	2 (3)	5 (14)
8	8 (30)	5 (28,931)	7 (3)	1 (10)
9	9 (35)	7 (18,082)	1 (2)	8 (12)
10	10 (40)	9 (25,315)	6 (2)	4 (13)

Figure 6: Sketch of quasi-level arrangement of U11¹⁰.**Table 11:** Factors and levels of STHX-CPBETWC used in RSM

Code	Factor (unit)	Level 1	Level 2	Level 3
		-1	0	1
A	P_c (mm)	20	30	40
B	Re	14,465	21,698	28,931
C	l_{et} (mm)	2	3	4
D	d_c (mm)	13	14	15

Table 12: Factors and levels of STHX-CPBSWT used in RSM

Code	Factor (unit)	Level 1	Level 2	Level 3
		-1	0	1
A	T_p (mm)	20	30	40
B	Re	14,465	21,698	28,931
C	T_a (mm)	2	4	6
D	T_w (mm)	10	12	14

Table 13: Geometric parameters of RRB-STHX for model validation (mm)

Parameter	d_o	P_t	d_t	L_b
Value	25	32	6	300

Table 14: Numerical results of STHX-CPBETWC obtained by TDML9

Case no.	Nu_{ETWC}	f_{ETWC}
1	205.55	0.5745
2	324.36	0.7594
3	497.50	1.0761
4	216.77	0.5708
5	307.12	0.6048
6	337.93	0.4284
7	219.46	0.5369
8	269.50	0.4011
9	349.92	0.4210

Table 15: Numerical results of STHX-CPBETWC obtained by TDML18

Case no.	Nu_{ETWC}	f_{ETWC}
1	205.55	0.5745
2	324.36	0.7594
3	497.50	1.0761
4	198.91	0.4580
5	298.36	0.5491
6	393.04	0.5944
7	204.75	0.4493
8	301.94	0.5153
9	343.66	0.3986
10	271.36	1.1199
11	277.37	0.5513
12	416.43	0.7471
13	216.77	0.5708
14	307.12	0.6048
15	337.93	0.4284
16	219.46	0.5369
17	269.50	0.4011
18	349.92	0.4210

Table 16: Numerical results of STHX-CPBETWC obtained by UDM

Case no.	Nu_{ETWC}	f_{ETWC}
1	301.38	0.9191
2	375.60	0.7260
3	228.08	0.6319
4	293.59	0.5137
5	356.19	0.4408
6	240.56	0.8079
7	295.18	0.5613
8	349.40	0.4683
9	233.77	0.4107
10	304.35	0.3864

Figure 7. It includes inlet extended region, heat transfer region, and outlet extended region. Hybrid mesh is used.

To simplify the numerical simulation, the following assumptions are made: the working fluid is water which

Table 17: Numerical results of STHX-CPBETWC obtained by RSM

Case no.	Level of parameter (actual value)				Response	
	A	B	C	D	Nu _{SWT}	f _{SWT}
1	−1 (20)	−1 (14,465)	1 (4)	1 (15)	271.36	1.1199
2	−1 (20)	−1 (14,465)	−1 (2)	−1 (13)	205.55	0.5745
3	−1 (20)	1 (28,931)	−1 (2)	1 (15)	389.87	0.6366
4	−1 (20)	1 (28,931)	1 (4)	−1 (13)	440.53	0.8619
5	−1 (20)	1 (28,931)	−1 (2)	−1 (13)	351.49	0.5413
6	−1 (20)	1 (28,931)	1 (4)	1 (15)	497.50	1.0766
7	−1 (20)	−1 (14,465)	1 (4)	−1 (13)	245.19	0.9018
8	−1 (20)	0 (21,698)	0 (3)	0 (14)	324.36	0.7592
9	−1 (20)	−1 (14,465)	−1 (2)	1 (15)	220.80	0.6724
10	0 (30)	−1 (14,465)	0 (3)	0 (14)	213.29	0.5491
11	0 (30)	0 (21,698)	0 (3)	0 (14)	291.21	0.5273
12	0 (30)	0 (21,698)	0 (3)	1 (15)	298.36	0.5491
13	0 (30)	1 (28,931)	0 (3)	0 (14)	370.88	0.5190
14	0 (30)	0 (21,698)	0 (3)	−1 (13)	285.27	0.5114
15	0 (30)	0 (21,698)	1 (4)	0 (14)	316.33	0.6295
16	0 (30)	0 (21,698)	−1 (2)	0 (14)	268.32	0.4372
17	1 (40)	1 (28,931)	−1 (2)	−1 (13)	323.91	0.3660
18	1 (40)	1 (28,931)	1 (4)	1 (15)	396.75	0.5215
19	1 (40)	−1 (14,465)	1 (4)	−1 (13)	214.09	0.5141
20	1 (40)	−1 (14,465)	−1 (2)	1 (15)	201.29	0.4265
21	1 (40)	1 (28,931)	1 (4)	−1 (13)	372.46	0.4839
22	1 (40)	−1 (14,465)	1 (4)	1 (15)	224.57	0.5517
23	1 (40)	1 (28,931)	−1 (2)	1 (15)	343.66	0.3986
24	1 (40)	0 (21,698)	0 (3)	0 (14)	282.11	0.4441
25	1 (40)	−1 (14,465)	−1 (2)	−1 (13)	193.35	0.3915

Table 18: Numerical results of STHX-CPBSWT obtained by TDML9

Case no.	Nu _{swt}	f _{swt}
1	199.97	0.4811
2	248.20	0.9150
3	267.76	1.1615
4	198.37	0.4216
5	247.38	0.8089
6	258.91	0.9292
7	195.20	0.3899
8	213.24	0.5465
9	257.81	0.8687

is continuous, Newtonian and isotropic; the gravity effect, thermal radiation, and viscous heating are negligible. The thermal-physical properties of water (density $\rho = 999.7 \text{ kg m}^{-3}$, thermal conductivity $\lambda = 0.574 \text{ W m}^{-1} \text{ K}^{-1}$, specific heat $c_p = 4191 \text{ J kg}^{-1} \text{ K}^{-1}$, and $\mu = 0.001306 \text{ (Pa s)}$).

5.2 Governing equations

The steady dimensionless mathematic equations for continuity, momentum, and energy are as follows:

Table 19: Numerical results of STHX-CPBSWT obtained by TDML18

Case no.	Nu _{ETWC}	f _{ETWC}
1	199.97	0.4811
2	349.02	0.9007
3	492.03	1.1542
4	198.37	0.4215
5	346.18	0.7891
6	467.53	0.9017
7	213.29	0.5465
8	361.65	0.8482
9	322.36	0.3638
10	267.76	1.1615
11	265.57	0.4624
12	450.76	0.8923
13	247.38	0.8089
14	362.06	0.9107
15	329.1	0.3967
16	257.54	0.8681
17	259.7	0.3716
18	366.15	0.5193

Continuity equation:

$$\frac{\partial(\rho u_j)}{\partial x_j} = 0 \quad (2)$$

Table 20: Numerical results of STHX-CPBSWT obtained by UDM

Case no.	Nu	f_{swt}
1	309.57	1.0008
2	453.10	1.1159
3	270.25	1.0204
4	325.56	0.6854
5	376.14	0.5411
6	252.59	0.9535
7	315.12	0.6580
8	356.72	0.5004
9	228.19	0.3805
10	287.96	0.3626

Figure 7: Sketch of computational domain and boundary conditions.

Momentum equation:

$$\frac{\partial(\rho u_i u_j)}{\partial x_j} = -\frac{\partial p}{\partial x_i} + \frac{\partial}{\partial x_j} \left(\mu_{\text{eff}} \left(\frac{\partial u_i}{\partial x_j} + \frac{\partial u_j}{\partial x_i} \right) \right) \quad (3)$$

Energy equation:

$$\frac{\partial(\rho c_p T u_j)}{\partial x_j} = \frac{\partial}{\partial x_j} \left(\lambda_{\text{eff}} \left(\frac{\partial T}{\partial x_j} \right) \right) \quad (4)$$

5.3 Boundary conditions

The 3-D, double-precision, pressure-based solver of Fluent is used [32]. SIMPLE algorithm is adopted; the second order upwind scheme is chosen to discrete momentum equation and energy equations; the second order difference scheme is used for the pressure [33]. The standard wall function method is adopted for the near-wall region.

Table 21: Numerical results of STHX-CPBSWT obtained by RSM

Case no.	Level of parameter (actual value)				Response	
	A	B	C	D	Nu_{swt}	f_{swt}
1	-1 (20)	-1 (14,465)	1 (6)	1 (14)	267.76	1.1615
2	-1 (20)	-1 (14,465)	-1 (2)	-1 (10)	199.97	0.4811
3	-1 (20)	1 (28,931)	-1 (2)	1 (14)	345.22	0.4937
4	-1 (20)	1 (28,931)	1 (6)	-1 (10)	454.54	0.9204
5	-1 (20)	1 (28,931)	-1 (2)	-1 (10)	332.73	0.4563
6	-1 (20)	1 (28,931)	1 (6)	1 (14)	492.03	1.1542
7	-1 (20)	-1 (14,465)	1 (6)	-1 (10)	251.76	0.9410
8	-1 (20)	0 (21,698)	0 (4)	0 (12)	349.02	0.9007
9	-1 (20)	-1 (14,465)	-1 (2)	1 (14)	205.28	0.5205
10	0 (30)	-1 (14,465)	0 (4)	0 (12)	239.20	0.7451
11	0 (30)	0 (21,698)	0 (4)	0 (12)	332.01	0.7252
12	0 (30)	0 (21,698)	0 (4)	1 (14)	346.18	0.7891
13	0 (30)	1 (28,931)	0 (4)	0 (12)	426.05	0.7160
14	0 (30)	0 (21,698)	0 (4)	-1 (10)	312.32	0.6487
15	0 (30)	0 (21,698)	1 (6)	0 (12)	390.02	1.0604
16	0 (30)	0 (21,698)	-1 (2)	0 (12)	264.01	0.4033
17	1 (40)	1 (28,931)	-1 (2)	-1 (10)	317.19	0.3384
18	1 (40)	1 (28,931)	1 (6)	1 (14)	491.48	0.9357
19	1 (40)	-1 (14,465)	1 (6)	-1 (10)	241.37	0.7578
20	1 (40)	-1 (14,465)	-1 (2)	1 (14)	195.20	0.3899
21	1 (40)	1 (28,931)	1 (6)	-1 (10)	431.03	0.7302
22	1 (40)	-1 (14,465)	1 (6)	1 (14)	268.31	0.9675
23	1 (40)	1 (28,931)	-1 (2)	1 (14)	322.36	0.3638
24	1 (40)	0 (21,698)	0 (4)	0 (12)	301.54	0.5710
25	1 (40)	-1 (14,465)	-1 (2)	-1 (10)	193.35	0.3628

All equations take the convergent criterions of relative residual of 1×10^{-4} except energy taking 1×10^{-6} .

The boundary conditions for computations shown in Figure 7 are described as follow:

- (1) Uniform temperature 283.15 K is assigned for the velocity inlet boundary.
- (2) The surfaces of the baffles are set as adiabatic.
- (3) Pressure outlet boundary is used for the exit.
- (4) The four boundary walls of the unit model are set as symmetry boundary conditions.
- (5) The temperature of heated tube wall is set as a constant, 350 K.

5.4 Thermal-hydraulic parameters

The Reynolds number Re can be obtained as:

$$Re = \frac{\rho D_h V_{in}}{\mu} \quad (6)$$

$$D_h = \frac{4(P_t^2 - \pi d_o^2/4)}{\pi d_o} \quad (7)$$

The average heat transfer coefficient, h , and the average Nusselt number, Nu , are obtained as follows:

$$h = \frac{c_p \rho V_{in} A_{in} (T_{in} - T_{out})}{A_o \Delta T} \quad (8)$$

$$Nu = \frac{h D_h}{\lambda} \quad (9)$$

$$\Delta T = \frac{T_{in} - T_{out}}{\ln \left(\frac{T_{in} - T_w}{T_{out} - T_w} \right)} \quad (10)$$

The friction factor is estimated by:

$$f = \frac{D_h}{L} \left(\frac{2 \Delta p}{\rho V_{in}^2} \right) \quad (11)$$

Figure 8: The result of model validation.

5.5 Validation and grid independence

For STHX-CPBETWC and STHX-CPBSWT, no experimental results can be found in open literatures. To validate the reliability of the numerical model, non-staggered tubes supported by RRB are computed and compared with the results obtained by Dong *et al.* [34]. The geometric parameters of the validation model are listed in Table 8. The computed results are plotted in Figure 8. It can be seen that the relative maximum deviation is within 7%, which shows the reliability of the numerical model adopted in this paper. In addition, mesh independency test is carried out to find the appropriate scheme (Table 13).

6 Results and discussions

According to the calculating formulas mentioned above, the results of STHX-CPBETWC and STHX-CPBSWT obtained by TDM, UDM, and RSM are listed in Tables 14–21, respectively. Analysis of variance (ANOVA) of Nu_{ETWC} and f_{ETWC} obtained by TDML9 and TDML18 is listed in Tables 22–25, respectively. ANOVA of Nu_{SWT} and f_{SWT} obtained by TDML9 and TDML18 is listed in Tables 26–29, respectively. ANOVA of Nu_{ETWC} , f_{ETWC} , Nu_{SWT} , and f_{SWT} obtained by RSM is listed in Tables 30–33, respectively.

Table 22: ANOVA of Nu_{ETWC} obtained by TDML9

Factors	DF	SS	Var	Rank
A	2	3.187	1.593	3
B	2	40.702	20.351	1
C	2	4.278	2.139	2
D	2	0.992	0.496	4
Error	0	0	0	
Total	8	49.158	24.91	

Table 23: ANOVA of f_{ETWC} obtained by TDML9

Factors	DF	SS	Var	Rank
A	2	35.866	17.933	1
B	2	0.119	0.060	4
C	2	20.097	10.048	2
D	2	3.534	1.767	3
Error	0	0	0	
Total	8	59.62	30.99	

Table 24: ANOVA of Nu_{ETWC} obtained by TDML18

Factors	DF	SS	Var	Rank
A	2	5.194	2.597	3
B	2	73.717	36.858	1
C	2	7.785	3.892	2
D	2	1.558	0.779	4
Error	9	0.38	0.04	
Total	17	88.68	44.20	

Table 25: ANOVA of f_{ETWC} obtained by TDML18

Factors	DF	SS	Var	Rank
A	2	70.15	35.07	1
B	2	0.75	0.37	4
C	2	38.99	19.49	2
D	2	6.90	3.45	3
Error	9	0.91	0.10	
Total	17	118.16	58.76	

Table 26: ANOVA of Nu_{SWT} obtained by TDML9

Factors	DF	SS	Var	Rank
A	2	1.442	0.721	3
B	2	30.259	15.130	1
C	2	12.508	6.254	2
D	2	0.397	0.199	4
Error	0	0	0	
Total	8	44.606	22.30	

Table 27: ANOVA of f_{SWT} obtained by TDML9

Factors	DF	SS	Var	Rank
A	2	15.04	7.52	2
B	2	1.64	0.82	4
C	2	84.71	42.35	1
D	2	2.40	1.20	3
Error	0	0	0	
Total	8	103.79	52.70	

Table 28: ANOVA of Nu_{SWT} obtained by TDML18

Factors	DF	SS	Var	Rank
A	2	2.379	1.190	3
B	2	70.746	35.373	1
C	2	25.124	12.562	2
D	2	0.771	0.385	4
Error	9	0.40	0.04	
Total	17	99.75	49.73	

Table 29: ANOVA of f_{SWT} obtained by TDML18

Factors	DF	SS	Var	Rank
A	2	28.77	14.39	2
B	2	0.68	0.34	4
C	2	168.11	84.06	1
D	2	4.56	2.28	3
Error	9	0.80	0.09	
Total	17	203.42	101.42	

Table 30: ANOVA of Nu_{SWT} obtained by RSM

Factors	DF	SS	MS	F	P
Model	14	192114.2	13722.44	98.1786	<0.0001
A	1	1034.828	1034.828	7.403783	0.0215
B	1	133546	133546	955.4682	<0.0001
C	1	46309.83	46309.83	331.3283	<0.0001
D	1	2212.355	2212.355	15.82852	0.0026
AB	1	80.65764	80.65764	0.577073	0.4650
AC	1	28.13198	28.13198	0.201273	0.6633
AD	1	33.42489	33.42489	0.239142	0.6354
BC	1	6247.454	6247.454	44.69804	<0.0001
BD	1	268.2549	268.2549	1.919257	0.1961
CD	1	841.5898	841.5898	6.021239	0.0340
A ²	1	176.4078	176.4078	1.262127	0.2875
B ²	1	2.456914	2.456914	0.017578	0.8972
C ²	1	110.5712	110.5712	0.791093	0.3947
D ²	1	48.30256	48.30256	0.345586	0.5697
Error	10	1397.702	139.7702		
Total	24	193511.9			

Standard deviation = 11.82.

 $R^2 = 99.28\%$ R^2 (adjusted) = 98.27%.**Table 31:** ANOVA of f_{SWT} obtained by RSM

Factors	DF	SS	MS	F	P
Model	14	1.55986	0.111419	51.55441	<0.0001
A	1	0.144421	0.144421	66.82493	<0.0001
B	1	0.002649	0.002649	1.225797	0.2941
C	1	1.290251	1.290251	597.011	<0.0001
D	1	0.072103	0.072103	33.36277	0.0002
AB	1	5.77×10^{-5}	5.77×10^{-5}	0.026698	0.8735
AC	1	0.005224	0.005224	2.417174	0.1511
AD	1	0.000252	0.000252	0.116477	0.7399
BC	1	1.33×10^{-5}	1.33×10^{-5}	0.006134	0.9391
BD	1	1.78×10^{-6}	1.78×10^{-6}	0.000825	0.9777
CD	1	0.034232	0.034232	15.83957	0.0026
A ²	1	0.000123	0.000123	0.056797	0.8164
B ²	1	0.000381	0.000381	0.176482	0.6833
C ²	1	0.000307	0.000307	0.141838	0.7143
D ²	1	0.001453	0.001453	0.672409	0.4313
Error	10	0.021612	0.002161		
Total	24	1.581472			

Standard deviation = 0.046.

 $R^2 = 98.63\%$ R^2 (adjusted) = 96.72%.

Table 32: ANOVA of Nu_{ETWC} obtained by RSM

Factors	DF	SS	MS	F	P
Model	14	154362	11025.861	304.573	<0.0001
A	1	8644.056	8644.056	238.779	<0.0001
B	1	124589	124588.957	3441.581	<0.0001
C	1	12829.25	12829.248	354.389	<0.0001
D	1	2504.488	2504.488	69.183	<0.0001
AB	1	1105.535	1105.535	30.539	0.0003
AC	1	1246.482	1246.482	34.432	0.0002
AD	1	345.1229	345.123	9.533	0.0115
BC	1	1682.67	1682.670	46.481	<0.0001
BD	1	395.4134	395.413	10.923	0.0079
CD	1	83.65259	83.653	2.311	0.1594
A ²	1	367.0631	367.063	10.140	0.0097
B ²	1	1.880495	1.880	0.052	0.8243
C ²	1	3.070484	3.070	0.085	0.7768
D ²	1	0.878836	0.879	0.024	0.8793
Error	10	362.0108	36.201		
Total	24	154724.1			

Standard deviation = 6.02.

 $R^2 = 99.77\%$ R^2 (adjusted) = 99.44%.**Table 33:** ANOVA of f_{ETWC} obtained by RSM

Factors	DF	SS	MS	F	P
Model	14	0.961007	0.068643	100.331	<0.0001
A	1	0.515545	0.515545	753.535	<0.0001
B	1	0.004872	0.004872	7.120	0.0236
C	1	0.27287	0.272870	398.835	<0.0001
D	1	0.036134	0.036134	52.815	<0.0001
AB	1	9.17×10^{-5}	0.000092	0.134	0.7219
AC	1	0.068483	0.068483	100.097	<0.0001
AD	1	0.014587	0.014587	21.321	0.0010
BC	1	2.79×10^{-5}	0.000028	0.041	0.8441
BD	1	4.41×10^{-6}	0.000004	0.006	0.9376
CD	1	0.003821	0.003821	5.585	0.0397
A ²	1	0.015292	0.015292	22.352	0.0008
B ²	1	0.00025	0.000250	0.365	0.5590
C ²	1	0.000218	0.000218	0.319	0.5848
D ²	1	9.6×10^{-5}	0.000096	0.140	0.7158
Error	10	0.006842	0.000684		
Total	24	0.967849			

Standard deviation = 0.026.

 $R^2 = 99.29\%$ R^2 (adjusted) = 98.30%.

From Tables 22–25, the effects of design factors on the thermal-hydraulic performance can be judged from the value of Variance (Var). For Nu_{ETWC} , the effectiveness of different factors follows the order: $B > C > A > D$. For f_{ETWC} , the effectiveness of different factors follows the order: $A > C > D > B$. This means that the Re has a significant effect on heat transfer rate, while the coil pitch has a significant effect on pressure drop. Similarly, for Nu_{SWT} , the effectiveness of different factors follows the order: $B > C > A > D$. For f_{SWT} , the effectiveness of different factors follows the order: $C > A > D > B$. This means that the Re is the most significant factor for heat transfer enhancement, while the tape amplitude is the most significant factor for reducing pressure drop. For designers, it is very important to identify which factor is the control

factor in the investigated range. The TDM just provides us a very efficient way. However, from ANOVA of Nu_{ETWC} , f_{ETWC} , Nu_{SWT} , and f_{SWT} obtained by RSM, the effectiveness of every factor cannot be obtained directly. In addition, it is also not applicable to obtain ANOVA for UDM. As a result, the designer may face the dilemma about which factor is the control factor.

After the results are obtained, the RBF based on 9 different experimental design methods is trained and tested. The comparison of error of Nu and f is shown in Tables 34–37, respectively. In the tables, the relative absolute error calculated by absolute of (CFD-Pre)/CFD% is shown in Figure 9–12. The sum absolute error is sum of the absolute of (CFD-Pre)/CFD%. In addition, for the column (time cost), it is assumed that the calculating

Table 34: Comparison of error of Nu_{ETWC} with different methods

Method	Spread	Max absolute error (%)	Sum absolute error (%)	Time cost (hour)
RBF + TDML9		33.39	404.47	45
RBF + TDML18		38.76	298.21	90
RBF + UDM		48.50	578.87	50
RBF + TDML9 + UDM		42.29	387.75	95
RBF + TDML18 + UDM	1	65.65	428.18	140
RBF + RSM		5.42	48.68	125
RBF + RSM + TDML9		9.80	40.02	170
RBF + RSM + TDML18		8.65	35.06	215
RBF + RSM + UDM		6.96	25.88	175
RSM	/	2.88	34.16	125
RBF + RSM	2	5.67	30.88	125
RBF + RSM	20	2.17	17.80	125

Table 35: Comparison of error of f_{ETWC} with different methods

Method	Spread	Max absolute error (%)	Sum absolute error (%)	Time cost (hour)
RBF + TDML9		55.99	565.78	45
RBF + TDML18		42.31	306.24	90
RBF + UDM		45.30	496.82	50
RBF + TDML9 + UDM		34.34	331.83	95
RBF + TDML18 + UDM	1	16.57	277.88	140
RBF + RSM		13.89	87.68	125
RBF + RSM + TDML9		12.28	68.51	170
RBF + RSM + TDML18		12.38	48.72	215
RBF + RSM + UDM		9.79	54.93	175
RSM	/	8.92	100.87	125
RBF + RSM	2	9.37	71.43	125
RBF + RSM	20	5.30	53.53	125

Table 36: Comparison of error of Nu_{SWT} with different methods

Method	Spread	Max absolute error (%)	Sum absolute error (%)	Time cost (hour)
RBF + TDML9		43.51	501.77	45
RBF + TDML18		51.26	337.29	90
RBF + UDM		41.46	551.86	50
RBF + TDML9 + UDM		52.57	395.92	95
RBF + TDML18 + UDM	1	90.93	573.30	140
RBF + RSM		6.60	47.09	125
RBF + RSM + TDML9		6.14	41.26	170
RBF + RSM + TDML18		7.78	28.81	215
RBF + RSM + UDM		6.74	31.68	175
RSM	/	6.82	120.41	125
RBF + RSM	2	4.01	37.74	125
RBF + RSM	20	5.60	38.21	125

Table 37: Comparison of error of f_{SWT} with different methods

Method	Spread	Max absolute error (%)	Sum absolute error (%)	Time cost (hour)
RBF + TDML9		57.26	718.97	45
RBF + TDML18		54.72	405.92	90
RBF + UDM		155.50	1761.26	50
RBF + TDML9 + UDM		44.06	383.38	95
RBF + TDML18 + UDM	1	90.86	484.92	140
RBF + RSM		8.60	82.71	125
RBF + RSM + TDML9		12.60	91.11	170
RBF + RSM + TDML18		9.88	36.41	215
RBF + RSM + UDM		10.57	57.54	175
RSM	/	14.52	214.42	125
RBF + RSM	2	8.97	78.68	125
RBF + RSM	20	10.55	85.08	125

time for all CFD runs are almost the same, that is 5 h per each.

It is always attracting for designers to know the thermal-hydraulic performance with the minimum expense. For the ten different prediction methods, the expense of

RBF + TDML9 is the minimum as only 9 CFD runs are needed which is only one third of that of RBF + RSM. However, from Tables 34–37, it can be found that the max absolute error and sum absolute error of RBF + TDML9 are very large. The max absolute error is 33.39% for Nu_{ETWC} ,

Figure 9: Comparison of relative error of Nu_{ETWC} obtained by different methods. The corresponding experimental model names from (a) to (l) can be obtained from the figure.

55.99% for f_{ETWC} , 43.51% for Nu_{SWT} , and 57.26% for f_{SWT} . For RBF + TDML18, the time cost is doubled compared with RBF +

TDML9. However, the max absolute error does not always decrease accordingly. The max absolute error is 38.76%

Figure 10: Comparison of relative error of f_{ETWC} obtained by different methods. The corresponding experimental model names from (a) to (l) can be obtained from the figure.

for Nu_{ETWC} , 42.31% for f_{ETWC} , 51.26% for Nu_{SWT} , and 54.72% for f_{SWT} . This indicates that the train data of RBF using TDM is not appropriate.

For RBF + UDM, the number of experiments is 10 which means the time cost of RBF + UDM is almost equal to that of RBF + TDML9. The max absolute error is 48.50%

Figure 11: Comparison of relative error of Nu_{SWT} obtained by different methods. The corresponding experimental model names from (a) to (l) can be obtained from the figure.

for Nu_{ETWC} , 45.30% for f_{ETWC} , 41.46% for Nu_{SWT} , and 155.50% for f_{SWT} . It can be found that the max absolute error does not decrease accordingly compared with

that of RBF + TDML9. The reason can be partly attributed to the scatter of design point in the design space of UDM.

Figure 12: Comparison of relative error of f_{SWT} obtained by different methods. The corresponding experimental model names from (a) to (l) can be obtained from the figure.

For RBF + TDML9 + UDM and RBF + TDML18 + UDM, it can be found that the predicted max absolute error is also very large, up to 65.65% for Nu_{ETWC} , 34.34%

for f_{ETWC} , 90.93% for Nu_{SWT} , and 90.86% for f_{SWT} . Particularly, the time cost of RBF + TDML18 + UDM is three times that of RBF + TDML9. However, the predicted

error becomes even larger. This seems contrary to the common sense of ANN that the more of train data, the more precision of the prediction. This indicates that the representativeness of training data is very important to the precision of RBF.

For RBF + RSM (spread = 1), it can be found that the predicted max absolute error is within the scope of engineering acceptance. The max absolute error is 5.42% for Nu_{ETWC} , 13.89% for f_{ETWC} , 6.60% for Nu_{SWT} , and 8.80% for f_{SWT} . The time cost of RBF + RSM is smaller than that of RBF + TDML18 + UDM. For RBF + RSM + TDML9, RBF + RSM + TDML18, and RBF + RSM + UDM, a similar finding can be found that the prediction precision does not improve when the number of train data increases. Particularly, if the parameter “spread” is adjusted, a distinct prediction precision can be reached. The max absolute error is from 5.67 to 2.17% for Nu_{ETWC} , from 13.89 to 5.3% for f_{ETWC} , from 6.60 to 4.01% for Nu_{SWT} , and from 10.55 to 8.60% for f_{SWT} . The sum absolute error is from 48.68 to 17.80% for Nu_{ETWC} , from 87.68 to 53.53% for f_{ETWC} , from 47.09 to 37.74% for Nu_{SWT} , and from 85.08 to 78.68% for f_{SWT} . This fact suggests that RBF trained with RSM only can be an effective, efficient, and affordable tool for thermal-hydraulic performance prediction of the STHX-CPBETWC and STHX-CPBSWT.

For RSM, it can be found that the predicted max absolute error is also within the scope of engineering acceptance. The max absolute error is 2.88% for Nu_{ETWC} , 8.92% for f_{ETWC} , 6.82% for Nu_{SWT} , and 14.52% for f_{SWT} . However, the sum absolute error of RSM is larger than that of RBF + RSM, 34.16% versus 17.80% for Nu_{ETWC} , 100.87% versus 53.53% for f_{ETWC} , 120.41% versus 37.74% for Nu_{SWT} , and 214.42% versus 78.68% for f_{SWT} . The reason can be explained from Figures 9–12. The RBF + RSM can approximate the true value for train data, while there still exists relative larger error for train data obtained by RSM.

Selecting representative points in the sampling space is essential for different DOE. Not all sampling points are necessary. Some representative test points can be selected from the comprehensive test points.

TDM is also known as orthogonal experimental design method. Orthogonal design is a design method to study multifactors and multilevels. It selects representative points according to orthogonality. It has two characteristics in selecting representative points: uniform dispersion and neat comparison. Uniform dispersion makes the test sites evenly distributed within the test range, so that each test site has sufficient representativeness. Therefore, even if all the columns in the orthogonal table are filled, the satisfactory results can be obtained. However, in order to

take care of the neat comparability, the test points of the orthogonal design cannot be fully evenly dispersed, and in order to achieve the neat comparability, the number of test points is relatively large. It must be tested at least once. For uniform design, especially in the case that the range of conditions varies greatly and multilevel tests are needed, uniform design can greatly reduce the number of tests. It only needs the same number of tests as the number of factor levels to achieve the test effect that orthogonal design can achieve at least one test. Uniform design only considers the full “uniform distribution” of the test sites within the test range, but does not consider the “neat comparable,” so the test results do not have the neat comparable of the orthogonal test results, and the test results are mostly processed by regression analysis method. Response surface analysis uses specific sampling method in the sample space. A multiple quadratic regression equation is used to fitting function relation between factors and response value. The optimal process parameters can be obtained through the analysis of regression equation, a statistical method to solve the problem of multivariate.

According to the different experimental design methods selected during the experiment, there are certain differences in the sample space obtained, resulting in a certain degree of difference in the data.

7 Conclusion

In this study, thermal-hydraulic performance prediction of two new parallel-flow STHXs using RBF based on different DOE is explored. The predicting efficiency and applicability of ten methods are discussed. Some main conclusions are drawn as follows:

- (1) The TDM not only can help us point out the significance of different factors, but also can save computing resource. However, thermal performance prediction using RBF + TDM is not applicable.
- (2) For RBF, it is not true that the more of train data, the more precision of the prediction.
- (3) The RBF + RSM behave best among the discussed ten prediction methods in terms of the accuracy of prediction. However, the parameter “spread” should be adjusted by trial and error to achieve a relative small error.

It must be emphasized that this does not mean the conclusions obtained above can be extrapolated to other heat exchangers. However, the authors encourage other

researchers to carry out similar tests to further check the findings of this paper. After all, the RBF + RSM can present good performance in the task of prediction of thermal-hydraulic performance of the STHX-CPBETWC and STHX-CPBSWT.

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