Engineering and Applied Science Research April – June 2017;44(2):84-89 Research Article

EASR

Engineering and Applied Science Research

https://www.tci-thaijo.org/index.php/easr/index

Published by the Faculty of Engineering, Khon Kaen University, Thailand

Optimum radii and heights of U-shaped baffles in a square duct heat exchanger using surrogate-assisted optimization

Kittinan Wansasueb, Nantiwat Pholdee and Sujin Bureerat*

Sustainable and Infrastructure Research and Development Center, Department of Mechanical Engineering, Faculty of Engineering, Khon Kaen University, Khon Kaen 40002, Thailand

Received September 2016
Accepted October 2016

Abstract

In this paper, optimum U-shaped baffles in a square channel heat exchanger using air as a working fluid were developed using surrogate-assisted optimization. The design problem is set to maximize heat transfer performance and simultaneously minimize pressure loss across the channel. Design variables determine the radii and heights of the baffles, whereas the optimization problem is treated as box-constrained optimization. The work in this paper is aimed at finding an appropriate surrogate model for designing such a heat exchanger system. Function evaluations are performed by means of computational fluid dynamics (CFD). The computations are based on the finite volume method and are carried out at a Reynolds number of 4000. It has been found that the use of U-shaped baffles as heat transfer enhancement devices improves the thermal performance of the heat exchanger. Comparative results reveal that the Kriging model is the most accurate surrogate model, however, the surrogate model giving the best result is support vector regression.

Keyword: Square duct heat exchanger, Optimization design, Surrogate models, U-shaped baffles, Differential evolution

1. Introduction

High performance devices or machines in industrial sectors are increasingly in demand [1]. Heat exchangers are a commonplace energy devices. There have been many techniques used to improve heat exchanger thermal performance. In order to get more compact heat exchangers, optimization is a means of responding to such requirements [2]. The techniques for heat transfer enhancement commonly used are to create turbulent fluid flow and reduce the thermal boundary layer near the wall. Nevertheless, this method in turn generates pressure losses requiring higher pump energy [3] at higher operating costs. In the use of baffles to generate turbulence, the first numerical work to predict the heat transfer characteristics of a duct was investigated by Patankar et al. [4].

In recent years, researchers investigated the shapes of baffles used with heat exchangers to increase heat transfer [5]. In heat exchanger optimization studies, heat transfer and pressure loss are generally set as design objective functions. Traditionally, objective function evaluations are carried out by means of computational fluid dynamics (CFD) in which each simulation is very time consuming. With such an obstacle, the use of surrogate-assisted optimization has been proposed to optimize heat exchangers. Vakili and Gadala [6] applied surrogate models, i.e., a radial basis function (RBF), Kriging model (KRG) and feed forward neural networks (FF neural network) for a conduction heat transfer problem to help reduce the number of function evaluations. Their validation experiments were conducted after developing an optimum solution, where a genetic algorithm (GA) [7] and particle swarm optimization (PSO) [8] were used as optimizers. A surrogate model can reduce computing time and give acceptable results compared with the use of the direct optimization method studied by Salviano et al. [9]. Jang and Chen [10] used an optimization method to design and optimize the louver angles of a louvered-fin heat exchanger, while a finite difference method was used to find numerical results. It can be seen from previous investigations that optimal geometries of heat exchangers to maximize thermal performance are the main focus of much research [11].

Researchers primarily used one surrogate model for their work. To our knowledge, the comparison of several surrogate models for designing a heat exchanger has yet to be studied. Therefore, this paper presents a comparative study of surrogate models for heat exchanger design. The U-shape baffles installed in a square duct heat exchanger are used as a case study. The design problem is set to simultaneously maximize heat transfer and minimize pressure loss. Differential evolution (DE), a popular meta-heuristic, is used as an optimizer. The results obtained from the various surrogate models are compared. Section 2 of this paper details optimization problem formulation and a CFD model. Section 3 discusses on the results and conclusions are drawn in Section 4.

*Corresponding author.
Email address: sujbur@kku.ac.th
doi: 10.14456/easr.2017.12

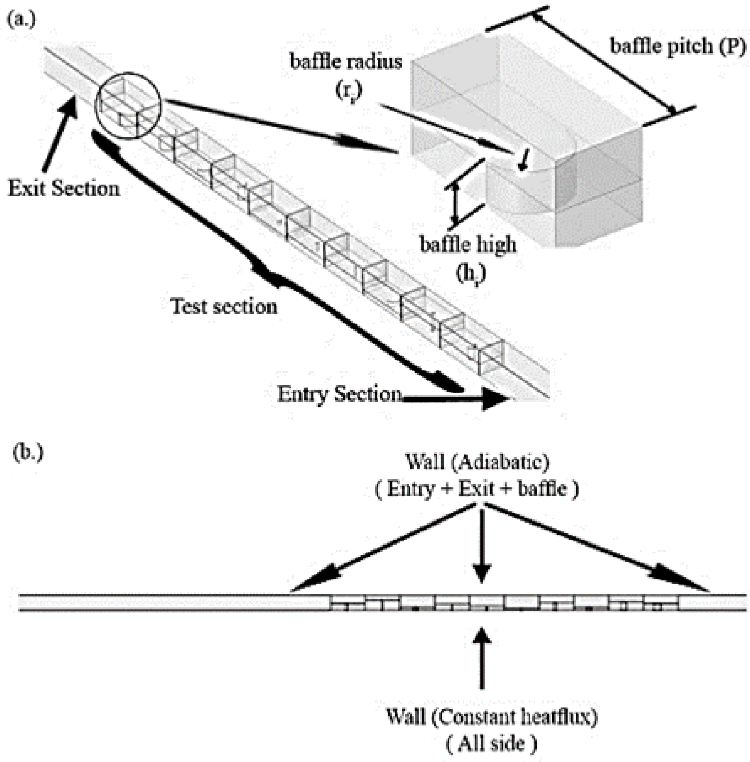

Figure 1(a) Schematic diagram of U-shape baffle and (b) wall boundary condition used.

2. **Problem definition and a mathematical model**

2.1 Baffle geometry and a design problem

The flow system of a square duct heat exchanger with U-shape baffles is shown in Figure 1a. The duct height (H) is set to 45 mm. The test section includes 10 U-shaped baffles with equal pitch (P) of 100 mm, starting at 50 mm from the inlet boundary of the test section. The baffle is 0.5 mm thick. Its radius (r_i) can be varied from 1 to 22 mm (one-half of duct width) and its height (h_i) can be varied between 1 and 34 mm (75% of channel high) during optimization. The duct height (H) is set to 45 mm. To ensure that the flow is fully developed, the entry and exit lengths are set to 2000 and 500 mm, respectively. For this geometry, the optimization design problem can be expressed as:

$$\textbf{Min}: f(\boldsymbol{x}) \tag{1}$$
$$subject\ to\ \ 0 \le x_i \le 34 \ \text{ mm} \quad \text{for } i = [\ 1,10\ ]$$
$$1 \le x_i \le 22 \ \text{ mm} \quad \text{for } i = [\ 11,20\ ]$$

where $\boldsymbol{x}= \{x_1,\ldots,x_{20}\}^T$ is a design vector. The elements of $\boldsymbol{x}$ from element 1 to 10 are used to specify the baffle heights, while elements 11 to 20 are the radii of the baffles. Since this work is a minimization problem with a single objective function, the objective function will be the value of the pressure loss divided by heat transfer rate (P/Q), which is a common practice in designing heat exchangers to maximize the ratio of heat transfer to frictional loss.

2.2 Boundary conditions

At the inlet, a uniform air velocity was developed with an inlet temperature of T_{in} = 300 K, while an atmosphere pressure outlet condition was applied at the exit. The test section walls are subjected to a constant heat flux of 600 W/m^2. A no slip wall condition is assumed throughout the channel. The entry, exit and all of the baffles are assumed to be adiabatic, as shown in Figure 1b.

2.3 Numerical methods

For the numerical work, the computational domain was explored using CFD. The Reynolds-averaged Navier-Strokes equations (RANS) are the governing equations of the duct flow model. It was computed by an iterative method called a generalized minimal residual method (GMRES) developed in 1986 by Saad Y and Schultz MH [12].The RNG k-ε turbulent model was applied in this study.

2.4 Optimization Procedure and surrogate models

The optimization method was applied with 4 types of surrogate models, i.e., Kriging model (KRG) [13] using a Gaussian correlation function with a zero-order polynomial regression function, Polynomial Response Surface (PRS) [14] with a second order polynomial function, radial basis function (RBF) [15] using a cubic spline kernel, and Supported Vector Regression (SVR) [16] using a radial basis function kernel. The MATLAB toolboxes DACE and LIBSVM were used for KRG and SVR [13, 16] respectively. A single objective differential evolution algorithm (DE/best/2/bin version), which is one of the top ranked optimizers [17], is used in this study. The optimization settings of DE are set to 0.7, 0.5 and 0.8 for crossover probability (p_c), scaling factor (F) and probability of choosing an element from an offspring in crossover (C_R), respectively. The number of generations and the population size are set as 500 and 100, respectively.

Table 1 Objective function value of sample point

Set no.	*f(X)*	*Set no.*	*f(X)*	*Set no.*	*f(X)*	*Set no.*	*f(X)*
1	49.2770	6	70.8227	11	210.0586	16	50.9861
2	75.6261	7	77.8390	12	85.4796	17	57.1346
3	45.3127	8	86.9229	13	123.0138	18	65.0601
4	140.5157	9	116.8853	14	122.1155	19	54.7569
5	41.8976	10	42.7534	15	70.8668	20	147.7912

Table 2 Optimum solutions of surrogate models

KRG		**PRS**		**RBF**		**SVR**	
Hight [mm]	Radius [mm]	Hight [mm]	Radius [mm]	Hight [mm]	Radius [mm]	Hight [mm]	Radius [mm]
34	11	19	12	18	11	19	8
5	19	12	7	18	12	10	5
29	7	33	4	18	12	21	7
11	6	18	7	18	11	14	3
4	3	12	13	18	11	5	16
15	16	13	19	17	12	32	7
14	15	1	5	18	11	4	6
26	18	32	1	17	11	25	9
8	18	10	20	17	11	20	2
27	5	2	1	17	11	4	16

The surrogate-assisted optimization with DE is performed in such a way that an Optimum Latin hypercube sampling technique [18] is used to generate 20 training design vectors. The actual function evaluations (CFD analyses) are then carried out. Having obtained 20 training points, a surrogate model can then be constructed. Then DE is employed to solve the optimization problem (1) where function evaluations are based on a corresponding surrogate predictor. Once an optimum solution is found, the actual function using CFD is determined for the solution. The aforementioned procedure will have a good design result while utilizing fewer resources to run the optimizer.

3. Results and discussion

3.1 Grid independence check

The flow domain was discretized using tetrahedral elements. A grid independence test was performed with different element densities, i.e., 158,192, 277,998, 550,227 and 1,005,984 elements. The grid independency test results are shown in Figure 2. It is illustrated that the value of P/Q varies less than 10% when comparing the 550,227 element and the 1,005,984 element models. Therefore, a grid density of 548,568 elements was used in the present study.

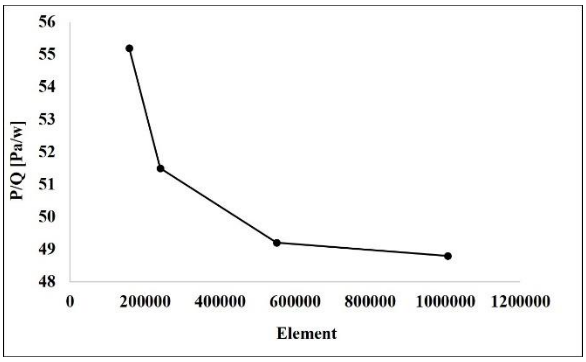

Figure 2 Grid independence check.

3.2 Comparative surrogate models

The ratio of pressure loss to heat transfer rate will be used as an objective function. Table 1 shows the values of such a ratio with the given training points obtained by means of Latin hypercube sampling. Afterwards, this data will be used to construct surrogate models that will then be used in an optimization process where DE is the optimizer.

The optimum solutions, i.e., the U-shape baffle geometries obtained from the various surrogate models, are illustrated in Figure 3 where their values are given in Table 2. It is shown that using different surrogate models result in completely different results.

Figure 4 presents the contour of pressure computed from the four optimum models in Figure 3. The highest value of pressure loss across the test section is from the KRG model at 7.49 Pa (Shown in Table 4). Other models have pressure losses between 3.71 to 4.92 Pa. Also, the heat transfer rate was calculated from the temperature difference between the inlet and outlet of the test section. Temperature contours of the optimum solutions are shown in Figure 5. All results show somewhat similar temperature differences between the inlet and outlet ranging from 32.9 K to 33.7 K. The heat transfer rate is approximately 0.1 W for all models.

Table 3 shows the comparative results of all four optimal solutions obtained from the four surrogate models. Examining the errors between the surrogate prediction and

Table 3 Optimum point for all surrogate models using DE compared with numerical results

***P/Q* [*Pa./W*]**			
Surrogate model	***Surrogate results***	***Actual numerical results***	***% Error***
KRG	67.9863	68.3100	**0.4739**
PRS	-1.0000	36.1666	97.2350
RBF	2.6689	44.6252	94.0193
SVR	-1.0000	**33.1423**	96.9827

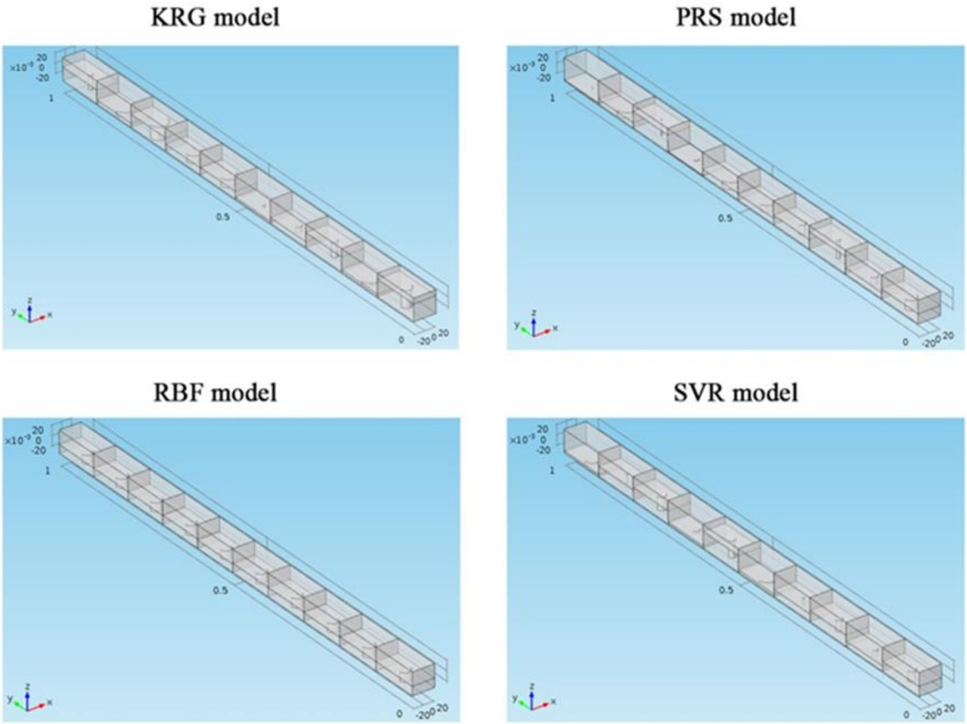

Figure 3 optimum geometry of U-shape baffles from surrogate models.

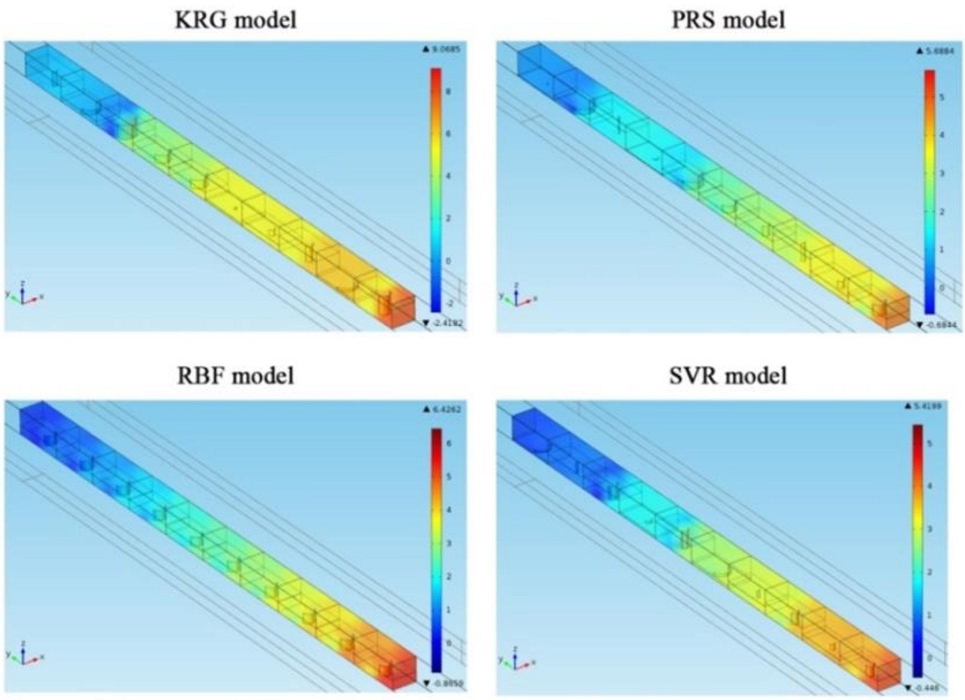

Figure 4 Pressure contour throughout a test section.

the actual function evaluations, it is shown that KRG is the only model that gives acceptable predictions. The other models fail to predict the values of pressure loss as detailed in Table 4. Nevertheless, when considering the optimum objectives, which are the ratio of pressure loss to the heat transfer rate, the SVR model gives a far better result compared to the more accurate KRG. This implies that there are uncertainties [19] in this design. As a result, when performing this type of design optimization, the use several surrogate models is recommended to rather than one model that gives the most accurate prediction results. All of results from the prediction model have dislocation compared with numerical results under the same conditions. Some results from the prediction model give irrational results. The percent error of results between surrogate model and numerical results are presented in Table 2. KRG gives precise results but the results are unusable in this case study because the dislocation value is very high. This may have resulted from

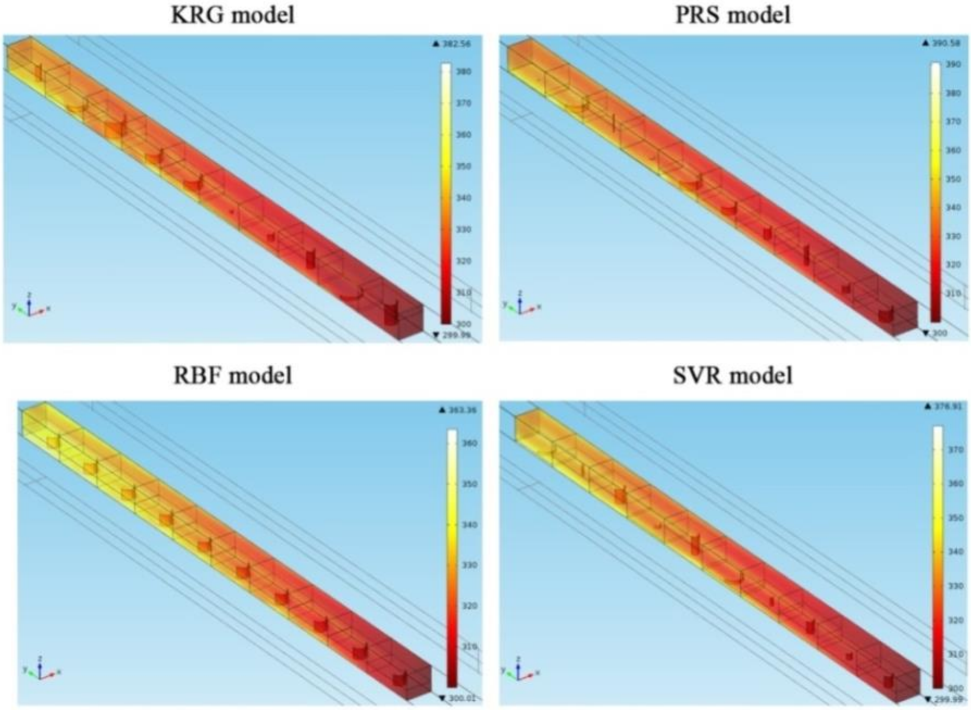

Figure 5 Temperature contours throughout a test section.

Table 4 Comparative heat transfer rates and pressure losses for all surrogate models using DE with numerical results

Surrogate model	Q *Surrogate result* [W]	Q *Actual numerical result* [W]	*% Error of Q*	P *Surrogate result* [Pa]	P *Actual numerical result* [Pa]	*% Error of P*
KRG	0.1088	0.1099	**0.9973**	7.4065	7.4906	**1.1231**
PRS	0.1179	0.1124	4.9646	0.1673	4.0538	95.8731
RBF	0.0779	0.1117	30.2320	9.6601	4.9834	93.8448
SVR	0.1112	0.1123	1.0263	-0.1443	3.7123	96.1129

the inappropriateness of correlations in the surrogate model or the number of points sampled might have been too low. However, the SVR model predicts the highest performance heat exchanger. The reasons for this is in the calculation of the heat transfer rate and pressure loss above, the term predicting pressure has a different result in the objective function, and SVR predicted pressure is loss very low while the heat transfer rate is similar. However, the KRG model should be used in practice because a predicted optimum solution is possible.

4. Conclusions

Optimization of U-shaped baffles in a square duct based on surrogate-assisted optimization was investigated in this work. Surrogate models including KRG, RBF, PRS and SVR were used while the optimizer was DE. The objective function was to simultaneously maximize heat transfer and minimize pressure loss along the channel. Comparative results show that KRG gives the most accurate prediction. However, using SVR gives the best design results. From the study, it is suggested that the use several surrogate models to perform surrogate-assisted optimization of this heat exchanger system is better than using one surrogate model alone. Moreover, it is also beneficial to employ a multiobjective optimizer to directly solve the multiobjective optimization problem. Also, several Reynolds numbers should be used in one CFD simulation ensuring that the resulting solution is practical. In the future work, the optimization problem should be designed as a true multiobjective optimization problem, while a multiobjective optimizer, e.g., multiobjective evolutionary algorithms (MOEAs) can be used to solve the design problem.

5. Acknowledgement

The authors are grateful for the support from SIRDC and the Master's degree scholarship from the Faculty of Engineering, Khon Kaen University.

6. References

[1] Alam T, Saini RP, Saini JS. Experimental investigation on heat transfer enhancement due to V-shaped perforated blocks in a rectangular duct of solar air heater. Energ Convers Manag. 2014;81:374-83.

[2] Godazandeh K, Ansari MH, Godazandeh B, Ashjaee M. Optimization of the angle of attack of delta-winglet vortex generators over a bank of elliptical-tubes heat exchanger. ASME 2013 International Mechanical Engineering Congress and Exposition, volume 8A: Heat Transfer and Thermal Engineering; 2013 Nov 15-21; San Diego, USA. USA: American Society of Mechanical Engineers; 2013. p. 1-10.

[3] Tang XY, Zhu DS. Flow structure and heat transfer in a narrow rectangular channel with different discrete rib

arrays. Chem Eng Process. 2013;69:1-14.
[4] Patankar SV, Liu CH, Sparrow EM. Fully developed flow and heat transfer in duct having streamwise-periodic variations of cross-sectional area. J Heat Tran. 1997;99(2):180-6.
[5] Chokphoemphum S, Chompookham T, Promvonge P. Heat transfer enhancement in a tube heat exchanger with a V-shape winglet turbulator. KKU Res J. 2014; 19(2):333-43. [In Thai].
[6] Vakili S, Gadala MS. Low cost surrogate model based evolutionary optimization solvers for inverse heat conduction problem. Int J Heat Mass Tran. 2013;56(1-2):263-73.
[7] Nakkaew P, Kantanantha N, Wongthatsanekorn W. A comparison of genetic algorithm and artificial bee colony approaches in solving blocking hybrid flow shop scheduling problem with sequence dependent setup/changeover times. KKU Eng J. 2016;43(2):62-68. [In Thai].
[8] Sangsawang C, Sethanan K. Hybrid particle swarm optimization with cauchy distribution for solving reentrant flexible flow shop with blocking constraint. KKU Eng J. 2016;43(2):55-61.
[9] Salviano LO, Dezan DJ, Yanagihara JI. Optimization of winglet-type vortex generator positions and angles in plate-fin compact heat exchanger: response surface methodology and direct optimization. Int J Heat Mass Tran. 2015;82:373-87.
[10] Jang JY, Chen CC. Optimization of louvered-fin heat exchanger with variable louver angles. Appl Therm Eng. 2015;91:138-50.
[11] Skullong S, Thianpong C, Jayranaiwachira N, Promvonge P. Experimental and numerical heat transfer investigation in turbulent square-duct flow through oblique horseshoe baffles. Chem Eng Process. 2016;99:58-71.
[12] Saad Y, Schultz MH. GMRES: A generalized minimal residual algorithm for solving nonsymmetric linear systems. SIAM J Sci Stat Comput. 1986;7(3):856-69.
[13] Lophaven SN, Neilson HB, Sondergaard J. DACE a MATLAB kriging toolbox. Technical report. Kongens Lyngby, Denmark: Technical University of Denmark; 2002. Report No.: IMM-TR -2002-12.
[14] Zhou Z, Ong Y, Lim M, Lee B. Memetic algorithm using multi-surrogates for computationally expensive optimization problems. Soft Comput. 2007;11(10): 957-71.
[15] Srisomporn S, Bureerat S. Geometrical design of plate-fin heat sinks using hybridization of MOEA and RSM. IEEE Trans Compon Packag Tech. 2008;31(2):351-60.
[16] Chang CC, Lin CJ. LIBSVM: a library for support vector machines. ACM Trans Intell Syst Tech. 2011; 2(3):1-27.
[17] Ao Y, Chi H. Differential evolution using opposite point for global numerical optimization. J Intell Learn Syst Appl. 2012;4:1-19.
[18] Pholdee N, Bureerat S. An efficient optimum Latin hypercube sampling technique based on sequencing optimisation using simulated annealing. Int J Syst Sci. 2015;46(10):1780-9.
[19] Ong YS, Z Zhou, Lim D. Curse and blessing of uncertainty in evolutionary algorithm using approximation. Congress on Evolutionary Computation. 2006 IEEE International Conference on Evolutionary Computation; 2006 Jul 16-21; Vancouver, Canada. USA: IEEE; 2006. p. 2928-35.