

# AN ONLINE APPROXIMATION ASSISTED OPTIMIZATION OF A NOVEL AIR-COOLED HEAT EXCHANGER

*Khaled Saleh, Graduate Research Assistant, Department of Mechanical Engineering, University of Maryland College Park, Maryland, USA;*

*Reinhard Radermacher, Professor, Department of Mechanical Engineering, University of Maryland College Park, Maryland, USA;*

*Vikrant Aute, Asst. Research Scientist, Department of Mechanical Engineering, University of Maryland College Park, Maryland, USA;*

*Shapour Azarm, Professor, Department of Mechanical Engineering, University of Maryland College Park, Maryland, USA*

**Abstract:** In this paper an online multiobjective approximation assisted optimization approach is used to design a novel air-cooled heat exchanger using multiscale simulation. Design optimization is performed using multiobjective genetic algorithm while the computational cost was reduced significantly by applying an online approximation technique. Higher model fidelity is achieved by applying the multiscale heat exchanger simulation method. The approach is based on the principle that when more points are sampled in the vicinity of the expected Pareto frontier (optimum design region), a fewer number of sample points will be eventually required for building a reasonably accurate metamodel. This approach uses a CFD technique coupled with  $\epsilon$ -NTU solver for heat exchanger performance evaluation. Comparing the results with offline approximation assisted optimization, the proposed online approximation assisted optimization approach resulted in better optimum results while reducing the computational time significantly.

**Key Words:** Air- cooled heat exchanger, online approximation, multiobjective optimization

## 1 INTRODUCTION

Computer simulations are being used in engineering design problems to replace costly and time consuming physical experiments. However, these simulations are usually computationally intensive as is the case of CFD simulations. In addition, coupling CFD simulations for new Heat eXchanger (HX) geometries with heat exchanger simulation tools makes the design of an optimum HX considerably more challenging. Indeed, it can become computationally prohibitive to use CFD simulations in the context of an optimization problem. This limitation can be resolved by the use of approximation assisted optimization. Approximation involves three main phases: (i) design of experiments (DOE) or a sampling phase, (ii) metamodel development phase, and (iii) metamodel verification phase. The DOE phase involves systematic probing of the prospective (and response) design space to generate a set of sample points for which the response from the computer simulation is evaluated. The results are then used to build a metamodel. A metamodel can be evaluated much more (often orders of magnitude) faster than an actual simulation. Finally, there is a verification phase in which a set of points is chosen to evaluate the goodness of the metamodel.

Approximation Assisted Optimization can be carried out online or offline. In online approximation assisted optimization, the metamodels for the objective and constraint functions are adaptively updated in concert with optimization (Nair and Keane, 1998; Farina 2001, 2002; Jin et al., 2001, 2002; Hong et al., 2003; Nain and Deb, 2003). Online metamodeling can gradually improve the metamodel accuracy (Jin, 2005) while optimization is ongoing. In offline approximation assisted approaches, optimization is performed based on a priori constructed metamodels used for objective and constraint functions (Papadrakakis et al., 1999; Wilson et al., 2001; Koch et al., 2002; Lian and Liou, 2004; Fang et al., 2004). In the area of HX optimization, most CFD studies have focused on segment level optimization. Few studies used approximation assisted optimization in HX optimization (Lee et al., 2001). Some existing methods have used curve fitting to correlate the response from CFD runs inside the optimization step. Other methods used DOE, metamodeling, and optimization in HX design applications (Jing et al., 2005; Park and Moon, 2005; Park et al., 2006).

The most recent work published in the area of HX optimization using multiscale simulation was based on adaptive DOE which was used to build offline metamodels for both air heat transfer coefficient (AHTC) and air pressure drop (ADP) (Aute et al., 2008 and Abdelaziz et al., 2010). The main advantage of using offline metamodels is the ability to work with different optimization objectives while using the same metamodel. In other words, based on accurate offline metamodels, different optimization problems can be solved with the same metamodels. However, the metamodels used should be globally accurate. That means more CFD runs are required to achieve a reasonable level of accuracy.

However, in many instances an optimization task is very narrowly defined. This means, in terms of optimization, both the objectives and the constraints are well known. In such cases, we just need to improve the performance of metamodels near the expected optimum region. Therefore, online metamodeling is a better choice and can find the optimum designs in a shorter time with reasonable accuracy.

In this paper, an online approximation assisted optimization is introduced to the area of HX design optimization. The approach integrates the use of CFD for segment level simulation with using the  $\epsilon$ -NTU model (Shah and Sekulic 2003) to evaluate the performance of the entire HX. Metamodels are used in the optimization to replace the expensive CFD simulation. The metamodels are updated in the direction of improving its performance in the region where the optimum solutions are expected to be. In this paper, the solutions from online approximation are compared with previous solutions from offline approaches. The online approximation approach outperforms the offline approximation approach in terms of reducing the computational time significantly and obtaining more accurate results.

The paper is organized as follows: Section 2 provides details of online approximation assisted optimization approach used in this paper. Section 3 offers a brief overview of the multiscale simulation approach. Section 4 summarizes the results obtained by applying multiobjective genetic algorithm to optimize the entire air-cooled HX. Section 5 draws conclusions based on the results.

## **2 ONLINE APPROXIMATION ASSISTED OPTIMIZATION**

In this section, the main idea of Online Approximation Assisted Optimization (OAAO) approach is briefly presented. The approach is iterative. In each iteration, an optimization is carried out using Multi Objective Genetic Algorithm (MOGA) based on the HX performance using CoilDesigner (Jiang et al., 2006) where metamodels are used for calculating AHTC and ADP. Then some selected optimum designs are used to update the metamodels in order to improve the accuracy of the metamodels in the expected optimum region. The approach described in this paper is generic. In other words, we can use any OAAO to update the metamodels. More details about the specific OAAO method can be found in (Saleh et al., 2010). In order to understand the approach further, in the following subsections, we will introduce a brief description of approximation terminology used in this paper.

## 2.1 Design of experiment

DOE is a basic step in any approximation technique. It involves how to sample the design space. There are many classifications for DOE methods. It can be classified as: classical methods, space filling methods, and adaptive methods (Simpson et al., 2001). In this paper, Maximum Entropy Design (MED) method (Shewry and Wynn 1987), which is considered as a space filling method, is used to select the initial design. For offline comparison, another adaptive method is used to build the offline metamodels. The adaptive method is called Space Filling Cross Validation Tradeoff (SFCVT) method (Aute et al., 2008).

## 2.2 Multiobjective optimization

A multiobjective optimization problem with  $m$  objective functions and  $j$  constraints is given as follows:

$$\begin{aligned} \text{Minimize} \quad & f_m(x) \quad m = 1, \dots, M \\ \text{Subject to} \quad & g_j(x) \leq 0 \quad j = 1, \dots, J \\ & x^{\text{lower}} \leq x \leq x^{\text{upper}} \end{aligned} \quad (1)$$

where  $x$  is a vector of design variables,  $f_m(x)$  is the  $m$ -th objective function to be minimized,  $g_j(x)$  is the  $j$ -th constraint, and  $x^{\text{lower}}$  and  $x^{\text{upper}}$  are the lower and upper bounds of  $x$ . More details on multiobjective optimization can be found in (Deb, 2001).

## 2.3 Kriging metamodel

Kriging (Cressie, 1993; Armstrong 1998) is an interpolative Bayesian metamodeling technique. It can be viewed as a linear predictor that estimates the unknown value of a response for an input sample point based on the known value of the response and the distance of the sample from the known design points. Kriging treats the response from a deterministic simulation as a realization of a stochastic process  $Y$ :

$$Y = \mu + Z(x) \quad (2)$$

where  $Y$  is the unknown response,  $\mu$  is a constant representing mean of all known response values and  $Z(x)$  represent the error which is modeled by a stochastic process with zero mean, variance of  $\sigma^2$ , and a non zero covariance. The quantity  $Y$  provides a global approximation of the design space while the term  $Z(x)$  creates a localized deviation so that the Kriging metamodel interpolates with respect to the previous observed points. More detailed introduction about the Kriging method can be found in Jones (2001).

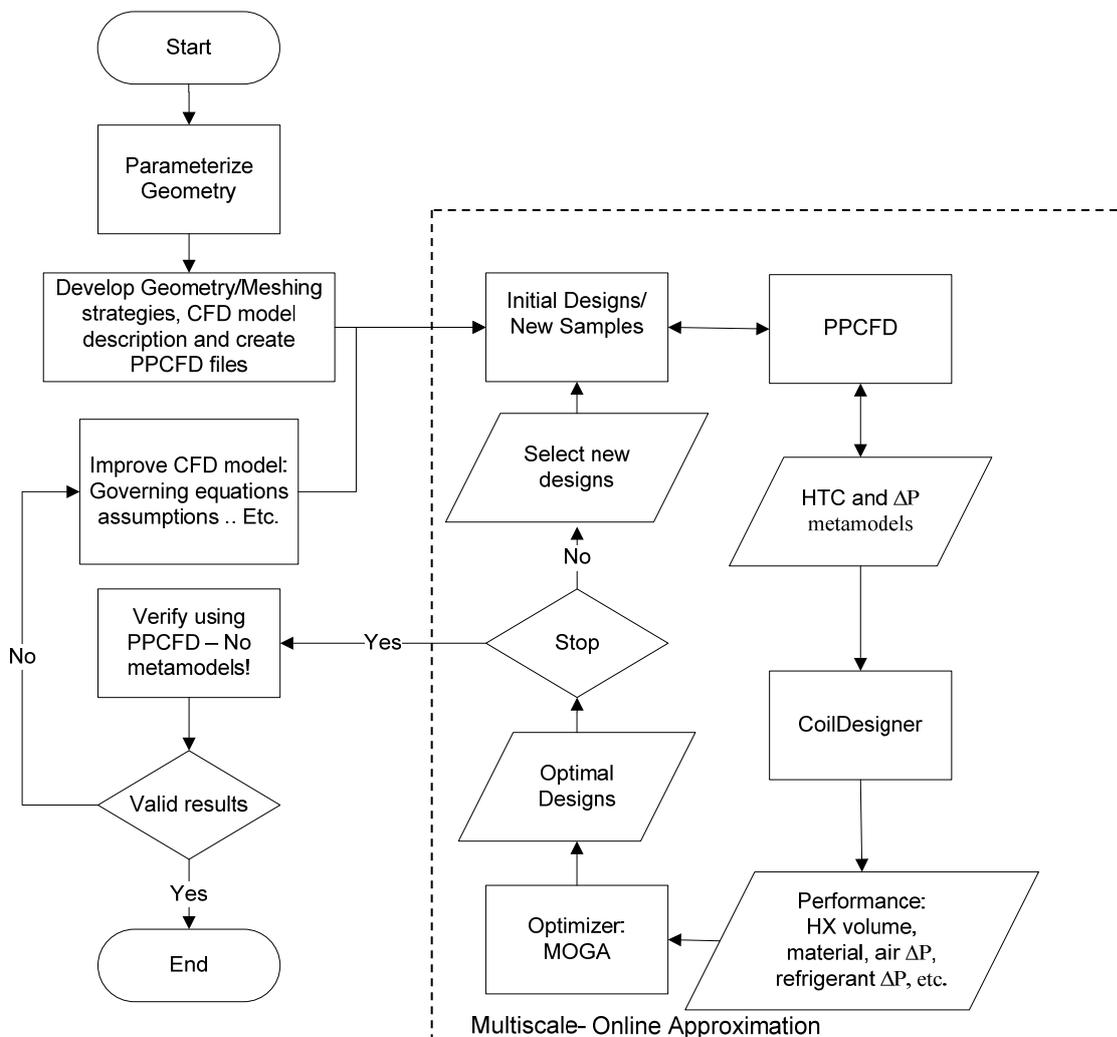
## 3 ONLINE APPROXIMATION MULTISCALE SIMULATION OPTIMIZATION

An OAAO approach is combined with multiscale simulation (Abdelaziz et al., 2010) in order to reduce the computational time. The new approach used here integrates CFD simulations with a conventional segment HX simulation tool to reduce the computational time while achieving reasonable accuracy. We used the commercial CFD package, Fluent® (Fluent 6.3.26) which was integrated with segment  $\epsilon$ -NTU solver, CoilDesigner (Jiang et al., 2006) to simulate the overall HX performance. CFD was used to calculate the segment AHTC and ADP which was used later in  $\epsilon$ -NTU solver to predict the entire HX performance.

The flowchart for the overall approach is presented in Figure 1. After developing a robust CFD model that is valid for the entire range of design variables, a set of initial designs is selected based on the maximum entropy DOE method. Afterwards, CFD runs using Parallel Parameterized CFD (PPCFD) was used.(Abdelaziz et al., 2010). The main steps in PPCFD can be listed as:

- Step-1: Read the parametric values of all the CFD cases.
- Step-2: Generate automatically Gambit® and Fluent® journal files.
- Step-3: Execute the journal files and performing post processing to summarize the results.

Based on PPCFD results, metamodels are built for both AHTC and ADP using the Kriging metamodeling method. Having the metamodels, CoilDesigner can be used to predict the AHTC and ADP based on the metamodels. After that, MOGA is used to optimize two design objectives: to minimize HX volume and minimize the air side total pressure drop based on CoilDesigner simulations. Subsequently, the obtained optimum design solutions are filtered using a filtering approach to select the new set of samples which are then used to update the metamodels. CFD simulations are performed for the new selected candidates using PPCFD. Thereafter, metamodels are updated. The previous steps are repeated several times until a certain stopping criterion is met. In this study, a limit on total number of CFD runs is used as the stopping criterion. Finally, the optimum solutions are verified using CFD simulations.



**Figure 1: Flowchart of the proposed online approximation multiscale approach**

The prescribed approach is generic. It can use any OAAO technique. In addition, it can be applied for any HX design with a great reducing in the computational time required. In the next section one example to apply the approach to find optimum designs of new generation of HXs with comparison with offline approximation solutions is presented.

#### 4 ONLINE APPROXIMATION ASSISTED OPTIMIZATION OF A NOVEL AIR-COOLED HEAT EXCHANGER

The online approximation multiscale simulation optimization approach described earlier in Section 3 was used to design a novel air-cooled HX. The optimization problem objectives for this design are to minimize HX volume and to minimize the air side pressure drop. These two objectives are conflicting. The HX design is based on segment configuration shown in Figure 2 ( Abdelaziz et al., 2010). There are six design variables as shown in Table 1.

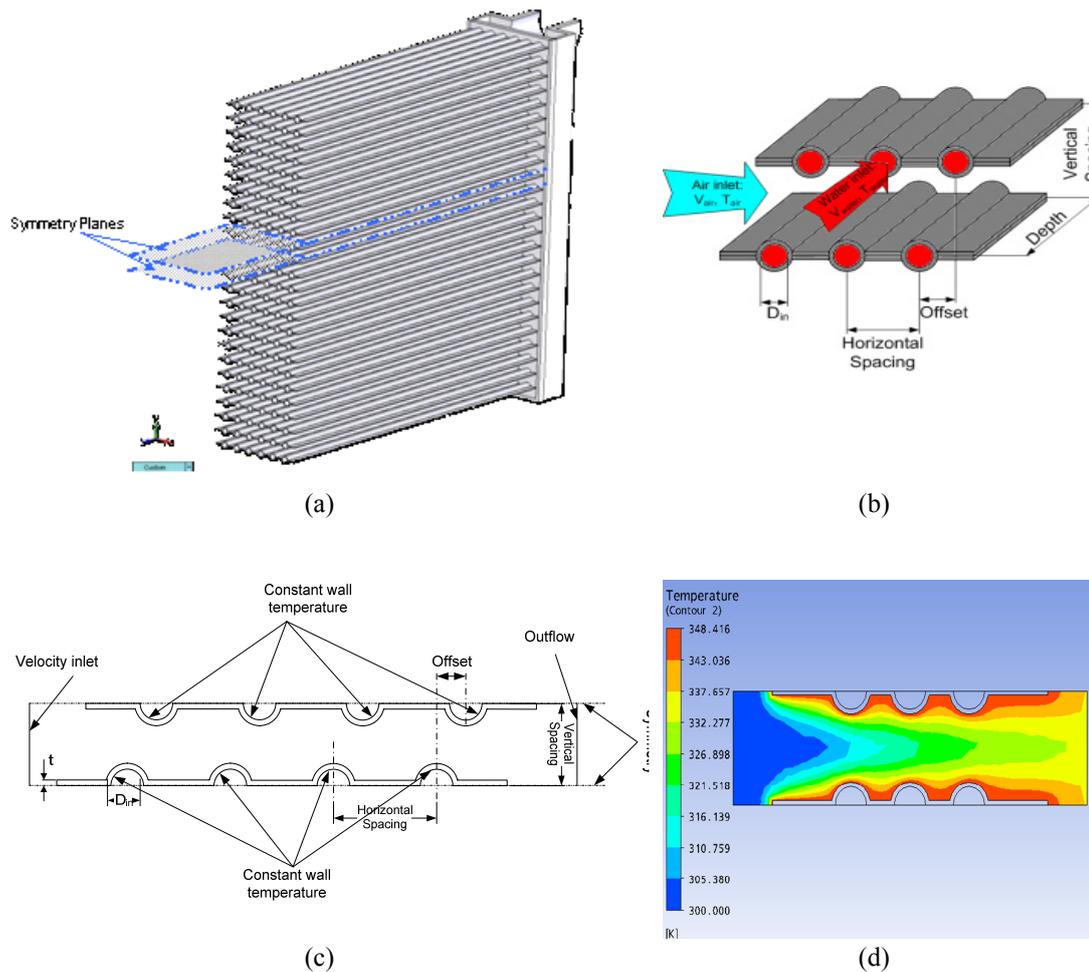
**Table 1: Design Variables for the heat exchanger segment**

Parameter	Range	Unit
Tube inner diameter ( $D_{in}$ )	0.2 – 0.7	mm
Horizontal Spacing (H.S.)	1.5 – 6.0	Fraction of $D_{out}$
Vertical Spacing (V.S)	2.0 – 4.0	Fraction of $D_{out}$
Number of Ports ( $N_p$ )	3 – 19	-
Air velocity ( $V_{air}$ )	0.5 – 3	m/s
Offset	0 – 1	Faction of H.S.

#### 4.1 Optimization Problem Description

The prescribed online approximation assisted multiobjective optimization approach used to optimize the design of a novel air-cooled HX. The optimization problem can be summarized as shown in Equation 3. The main objectives are to minimize both the HX volume and the air side pressure drop. This is subjected to certain constraints on the pressure drop for both air and refrigerant sides. Also, the aspect ratio which is the ratio between the tube length (L) and the coil height ( $N_t \times V.S$ ) is constrained. There is one more limitation on the HX volume.

$$\begin{aligned}
 & \underset{x}{\text{Minimize}} && \text{HX Volume} \\
 & \underset{x}{\text{Minimize}} && \Delta P_{air} \\
 & \text{Subject to} && \Delta P_{air} < 100 \text{ Pa} \\
 & && 0.25 < \text{Aspect Ratio} < 4 \\
 & && 1000 < Q < 1050 \text{ W} \\
 & && \text{HX Volum} < 240 \text{ cm}^3
 \end{aligned} \tag{3}$$



**Figure 2: (a) Air to refrigerant heat exchanger, (b) heat exchanger segment, (c) Schematic, and (d) Computational Domain and sample results (Saleh et al., 2010)**

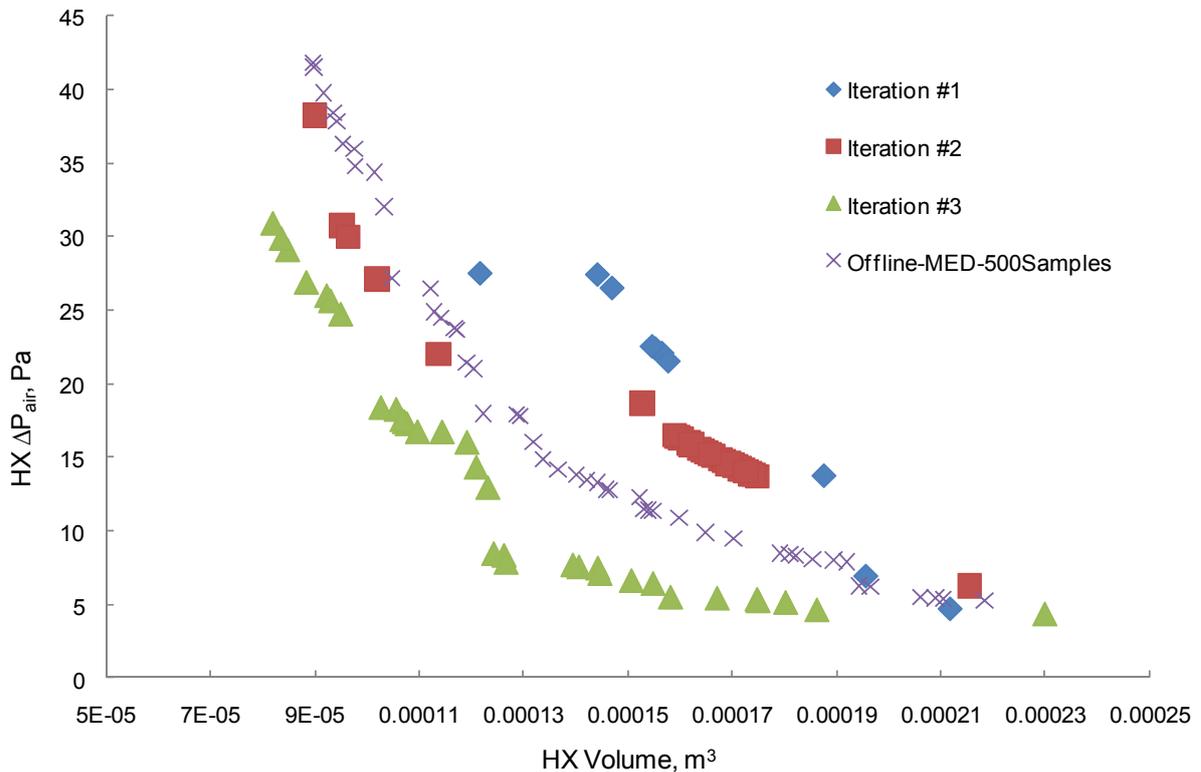
## 4.2 Solution Procedure

The solution starts with CFD model development that is valid for the entire design space. Then MED method was used to generate a set of initial designs. In this particular problem, we used 65 samples in order to fill the design space boundaries with initial designs. Then, PPCFD runs. The results are used to build a metamodels for both ADP and AHTC. Afterward, MOGA runs with a population of 150 with 200 generations to find the optimum designs. The objectives/constraints evaluations are based on CoilDesigner to evaluate the performance of the entire HX. In lieu of CoilDesigner runs, metamodels are used to predict both ADP and AHTC on the segment level. After obtaining some intermediate optimum solutions, OAAO method is applied to filter some of the optimum solutions and select the next set of samples to update the metamodels. The results are presented at intermediate iterations in the next section.

## 4.3 Results

In this section, the results at different number of samples are presented. Firstly, after running MOGA based on 65 samples, the optimum solutions, i.e., the approximated Pareto solutions,

are presented as Iteration #1 as shown in Figure 3. Next, after different updates of the metamodells based on intermediate MOGA runs, the results are presented for a total number of samples of 95 and 120 as Iteration #2 and Iteration #3 respectively. As it is apparent from the results, better solutions can be obtained using fewer number of CFD simulations. To compare the results with offline multiscale approximation approach, we built offline metamodells for both AHTC and ADP using 500 samples based on MED method. As it can be depicted from the results, online multiscale approximation approach resulted in better optimum designs compared with offline approach based on MED designs. Approximately 76% CFD simulations are saved when using the online multiscale approximation approach.



**Figure 3: Online multiscale approximation results at different iterations and comparison with Offline results using MED**

In addition, the online multiscale approximation approach was compared with offline approach based on adaptive sampling. The adaptive sampling technique used in this comparison is SFCVT as mentioned earlier. As it can be illustrated from Figure 4, the results are comparable. However using online multiscale approximation approach, we can save 60% of the computational simulations.

#### 4.4 Pareto Solution Verification

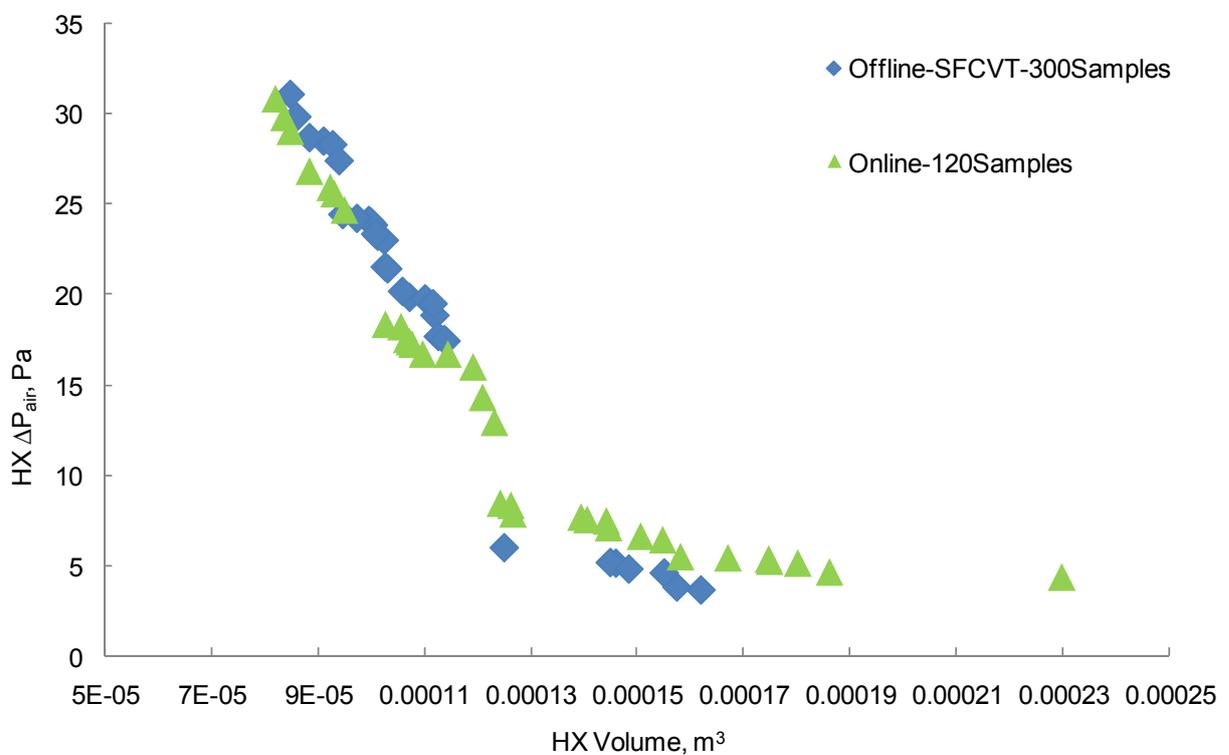
In order to verify the accuracy of the obtained results, all Pareto solutions were verified using CFD runs. The errors in predicting air side pressure drop and air heat transfer coefficient are summarized in Table 2. The definition of error metrics used is given in Equation 4 where  $y(x)$  is the actual response while  $\hat{y}(x)$  is the predicted response using the metamodells. By examine the results, it is clear that the performance of the metamodells are improved by adding more samples, yet, the performance of online multistage approximation gives acceptable results when comparing with offline sampling using less number of samples as the case for SFCVT with 300 samples. This is the main advantage of using online

approximation. In case of limitation in the computational resources online multistage approximation gives reasonably accurate results in shorter time. By adding more samples the accuracy of the obtained results is improved.

$$\begin{aligned} \text{Error}_i &= y(x_i) - \hat{y}(x_i) \\ \text{RError}_i &= \frac{|y(x_i) - \hat{y}(x_i)|}{y(x_i)} \times 100\%, i = 1, \dots, n \\ \text{RMSE} &= \sqrt{\frac{1}{n} \sum_{i=1}^n \text{Error}_i^2} \\ \text{RRMSE} &= \sqrt{\frac{1}{n} \sum_{i=1}^n \text{RError}_i^2} \% \end{aligned} \tag{4}$$

**Table 2: Pareto optimal designs verification results**

Method (Number of Samples)	RMSE		RRMSE	
	ADP ( Pa)	AHTC ( W/m <sup>2</sup> K)	ADP %	AHTC %
<b>Online (120)</b>	3.80	18.32	16.7	14.82
<b>Offline-MED (500)</b>	8.78	2.56	20.78	2.698
<b>Offline-SFCVT (300)</b>	8.58	15.51	30.41	12.75



**Figure 4: Online multiscale approximation results versus offline multiscale approximation results based on adaptive sampling**

## 5 CONCLUSIONS

A new approach for online multiscale approximated assisted optimization of heat exchanger is presented. The approach combines adaptive update of metamodels for air heat transfer coefficient and air pressure drop on the segment level with the entire heat exchanger simulation for new generation of air-cooled heat exchangers. The approach resulted in a significant reduction of computational cost compared with offline approximation techniques. The accuracy of the results is comparable with offline approximation results. The online multiscale approximation approach can save more than 60 % of the computational time required to obtain similar results as the offline multiscale approximation techniques. The approach is generic in nature and can be applied to any similar heat exchanger optimization.

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