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ABSTRACT

This paper presents a comparison between different multiobjective optimization approaches that can be used to optimize the design of thermal equipment. Plate heat exchanger is taken as case study to apply different optimization techniques. The thermal-hydrodynamic characteristics of single phase turbulent flow in chevron-type plate heat exchangers with sinusoidal-shaped corrugations have been used in this paper. The computational domain contains a corrugation channel and the simulations adopted the shear-stress transport (SST) $\kappa$-$\omega$ model as the turbulence model. Two different approximation assisted optimization approaches are tested. Offline approximation assisted optimization, and online approximation assisted optimization are compared to optimize plate heat exchanger design. For both approximation techniques (offline and online), design optimization is performed using multiobjective genetic algorithm based on meta-models that are built to represent the entire design space. In offline approximation assisted optimization, samples are added just to improve the metamodels performance in the expected optimum region. Approximated optimum designs are validated using computationally expensive actual CFD simulations. Finally, a comparison between offline and online approximation assisted optimization is presented with guidelines to apply both approaches in the area of heat exchanger design optimization. The methods presented in this paper are generic and can be applied to optimize different types of heat exchangers, electronic cooling devices and other thermal system components.

1. INTRODUCTION

Developing an optimized compact heat exchanger is crucial task for many applications. In general, two objectives mainly are considered while designing a heat exchanger for naval and aeronautics applications. These two objectives focus on minimizing heat exchanger volume as well as minimizing the total pressure drop. Conventionally, designers used exhaustive search and other trial-and-error methods to find the best heat exchanger design. However, it is very difficult to apply exhaustive search if the heat exchanger model is computationally expensive, i.e., it takes several hours or even days to run one single simulation. Also, it is computationally prohibitive in cases of dealing with large number of design variables and design objectives. In addition, using some conventional optimization approaches such as multiobjective genetic algorithms and other heuristic optimization techniques can help reduce the total number of simulations needed but still it is not feasible to apply these techniques for large scale design problems. Therefore, using approximation assisted optimization techniques can help to reduce the computational time associated with the optimization process. Plate heat exchangers (PHXs) are widely used in the area of refrigeration, heat pumping, food industry and chemical processing. High thermal performance, ease of maintenanous, compactness and the ability to work with small temperature differences are the main advantages of using PHXs (Wang et al., 2007). Recently CFD models are being used to optimize different type of heat exchangers (Abdelaziz et al., 2010). PHXs optimization studies can be found in the recent literature reflecting the increasing interest in the practical implementation of such systems (Kanaris et al., 2009; Han et al., 2011). Kanaris et al. (2009) searched the optimal
design of PHXs with undulated surfaces using CFD techniques. An objective function that combines heat transfer together with friction losses accounting for the energy costs was employed in the optimization procedure using response surface methodology. However, the optimal designs of their study cannot be necessarily extrapolated to the cases of PHXs with sinusoidal-shaped corrugations. Recently offline approximation assisted optimization (AAO) technique was used to optimize single phase turbulent flow in chevron-type PHX with sinusoidal corrugations (Han et al., 2011). However, AAO is computationally expensive as it requires building globally accurate metamodels.

The objective of this paper is to present the method and results of a study on the optimal design of PHX using a multi-objective genetic algorithm based online approximation assisted optimization (OAAO) and compare the results with offline based approximation assisted multiobjective optimization approach. The results are verified using CFD simulations. The paper is organized as follows: Section 2 offers details of the offline and online approximation assisted optimization approaches used in this paper. Section 3 provides a brief overview of the PHX CFD model. Section 4 summarizes the results obtained by applying the online approximation assisted approach to optimize the PHX and compare the results with offline approximation approach with CFD verification. Section 5 draws conclusions based on the results.

2. Background and Terminology

In this section, the main steps involved in approximation assisted optimization approaches are briefly described.

2.1 Approximation Assisted Optimization

Approximation assisted optimization techniques are used to replace the computationally expensive function evaluations with much faster evaluations using metamodels. Metamodels are simplified mathematical formulations used to describe an unknown physical relation or to substitute a more complex model such as CFD simulations. Typically, approximation assisted optimization starts with, Design of Experiment (DOE), an initial set of sample points in the design space. These points are then used to construct metamodels for the objective and constraint functions of an optimization problem. Finally, an optimizer such as Multiobjective Genetic Algorithm (MOGA) is used based on the metamodel evaluations to find the optimum designs. Approximation assisted optimization can be classified into two types: offline and online. In offline approximation assisted optimization (AAO), all samples are selected before running the optimizer. Then metamodels are built for all objectives and constraints. These metamodels are verified using random samples. If these metamodels are accurate, the optimizer will run based on these metamodels. Otherwise, more samples are added to improve the metamodels’ accuracy. Obviously, there is no feedback from the optimizer to update the samples (Papadrakakis, 1999). However, in online approximation assisted optimization (OAAO), metamodels are updated gradually during the optimization to improve the metamodels performance in the expected optimum region (Nain and Deb, 2003). The difference between AAO and OAAO is shown in Figure 1.

**Figure 1:** Comparison between approximation assisted optimization approaches (a) offline and (b) online.

International Refrigeration and Air Conditioning Conference at Purdue, July 16-19, 2012
2.2 Design of Experiment (DOE)
DOE is a first step in any approximation technique. It is a systematic approach to sample the design space. There are many types of DOE methods. They 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), a space filling method, is used to select the initial design.

2.3 Multiobjective Optimization
Multiobjective optimization formulations are used for many engineering design problems. An results of a multiobjective optimization problem is generally a set of solutions called Pareto optimum solutions (Deb, 2001). A multiobjective optimization problem can be formulated as follows:

\[
\begin{align*}
\text{minimize} & \quad f_m(x) \quad m = 1, \ldots, M \\
\text{subject to} & \quad g_j(x) \leq 0 \quad j = 1, \ldots, J \\
& \quad x^{\text{lower}} \leq x \leq x^{\text{upper}}
\end{align*}
\]

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 \( x \). In the current paper, Multi-Objective Genetic Algorithm (MOGA) is used as the optimizer (Deb, 2001).

2.4 Kriging Metamodeling Approach
Kriging is an interpolative Bayesian based metamodeling technique (Cressie, 1993). It can be viewed as a linear predictor that estimates an unknown value of a response for an input sample point based on the known values 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:

\[
Y = \mu + Z(x)
\]

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 observed (known) points. A more detailed introduction about the Kriging method can be found in Jones (2001).

3. Plate Heat Exchanger Segment Model
An essential step in AAO is using a parallel parameterized CFD (PPCFD) approach (Abdelaziz et al., 2010) to automatically read the normalized design variables and then generate the corresponding Gambit® journal files. The PHX segment model is presented in Figure 2. Mesh refinement near the boundaries (boundary layer inflation) is applied. Also, a finer mesh is applied in locations where higher temperature gradients are expected, such as near the plate walls, as shown in Figure 3. More details about the model can be found in Han et al. (2011). A small segment of the PHX is simulated to calculate both the pressure drop per unit length and the heat transfer coefficient. Steady state, 3-D model with pressure based solver and implicit scheme is used to solve the computational domain. In this case, the shear-stress transport (SST) \( \kappa-\omega \) model was chosen as the turbulence model because of its robustness and the capability of combining both \( \kappa-\omega \) model and \( \kappa-\varepsilon \) model, which makes it more accurate and reliable for a wide range of flow applications. It should be noted that in order to correctly utilize the SST \( \kappa-\omega \) model, the mesh quality near the wall boundary must be sufficiently fine so that the dimensionless wall distance \( y^+ \) presented in Equation 3 is of the order of 1 as imposed by the turbulent model (Kanaris et al. 2009; ANSYS FLUENT 12.0 Documentation, 2009).

\[
y^+ = \rho \sqrt{\tau_w / \mu_y / \mu}
\]
The PHX segment thermal and hydraulic performances are evaluated in terms of heat transfer coefficient $h$ as given in Equation 4 and pressure drop per unit length $\Delta P/L$ where $L$ is the segment length and $\Delta P$ is reported directly from CFD simulation as given in Equation 5.
From the CFD simulation mass flow rate ($\dot{m}$) and outlet temperature ($T_{out}$) is calculated for a given inlet temperature ($T_{in} = 295$ K) and wall temperature ($T_w = 300$ K) and inlet design variables.

### 4. Plate Heat Exchanger Segment Optimization

The schematic of the PHX segment is shown in Figure 2. The goal is to find optimized designs that have maximum heat transfer coefficient $h$ and minimum pressure drop per unit length $\Delta P/L$. The different design variables that define the PHX segment performance are shown in Figure 2. The four design variables are defined in Table 1. The corresponding computational domain is shown in Figure 3. The heat transfer coefficient and the PHX segment pressure drop are obtained by solving the continuity, the momentum, and the energy equations using a commercially available CFD tool such as Fluent®. For different designs, the solutions are obtained for a fixed wall temperature, $T_w = 300$ K, and constant coolant inlet temperature $T_{in} = 295$ K with variable coolant flow rate. Water is used in this study as the working fluid.

<table>
<thead>
<tr>
<th>Design Variable</th>
<th>Lower limit</th>
<th>Upper limit</th>
</tr>
</thead>
<tbody>
<tr>
<td>$b$ [mm]</td>
<td>3.18</td>
<td>6.35</td>
</tr>
<tr>
<td>$\beta$</td>
<td>22°</td>
<td>68°</td>
</tr>
<tr>
<td>$p$ [mm]</td>
<td>9.50</td>
<td>38.0</td>
</tr>
<tr>
<td>$u$ [m/s]</td>
<td>0.1</td>
<td>1.2</td>
</tr>
</tbody>
</table>

### 4.1 PHX Segment Optimization Problem Definition

In this study individual metamodels are developed for each response, i.e., for heat transfer coefficient $h$ and pressure drop per unit length $\Delta P/L$. The optimization problem can be summarized as shown in Equation 6. The first objective is to maximize the heat transfer coefficient. The second objective is to reduce the pressure drop thus reducing the pumping power required.

\[
\begin{align*}
\text{maximize} & \quad h \quad [W/m^2K] \\
\text{minimize} & \quad \Delta P/L \quad [Pa/m] \\
\text{subject to:} & \quad h \geq 5000 \quad W/m^2K \\
& \quad \Delta P/L \leq 100 \quad kPa/m
\end{align*}
\]

### 4.2 Online Approximation Assisted Optimization Steps

Figure 1 shows the difference between offline and online approximation assisted optimization approaches. For OAAO, the stopping criterion is the maximum number of available simulations. The steps in OAAO are as follows:

\[
\begin{align*}
Q &= \dot{m} \cdot C_p \cdot (T_{out} - T_{in}) \\
\text{LMTD} &= \frac{(T_{in} - T_w) - (T_{out} - T_w)}{\ln{(T_{in} - T_w)/(T_{out} - T_w)}} \\
\Delta P &= P_{in} - P_{out}
\end{align*}
\]
Step 1: Generate an initial set of design points using the maximum entropy design method and observe the corresponding responses for the heat transfer coefficient \( (h) \) and the fluid pressure drop per unit length inside the PHX segment \( (\Delta P/L) \).

Step 2: Develop a metamodel for each objective; i.e., \( h \) and \( \Delta P/L \).

Step 3: Formulate a multiobjective optimization problem based on the metamodels and solve it using MOGA.

Step 4: From all Pareto points, select points to improve the metamodel accuracy in the expected optimum region and to improve the diversity of the optimum designs both in the design space and objective space. The two extreme points in the objective space are selected to improve the diversity.

Step 5: Evaluate the true response (i.e., run the simulation) for the newly chosen points and then go to Step 2.

Step 6: Repeat Step 2 to Step 5 until a limit on the number of function calls is achieved.

More details regarding OAAO approach and the selection criterion mentioned in Step 4 can be found in Saleh et al. (2010).

4.3 Results and Discussion

Two different metamodels were built for the two responses viz., \( h \) and \( \Delta P/L \). The initial design comprising of 50 points was generated using the MED method and then OAAO method was used to sample additional 62 additional points in 6 runs as presented in Figure 4. In each run, metamodels were built then optimizer was run based on these metamodels and finally Pareto solutions were filtered to select the next samples to update the current metamodels. For AAO, a set of 200 samples was generated before building the metamodels using MED method.

As it can be seen from Figure 4, the performance of the OAAO is improved gradually by adding more samples in the expected optimum region. Compared with AAO, OAAO can add more samples near the Pareto frontier and can find better designs while reducing more than 40% of the computational cost. Consequently, Pareto obtained from OAAO appears to be better than Offline AAO especially in the right upper corner as shown in Figure 4. Generally speaking, having more sample points in the expected optimum region assistance to improve the performance of both methods. The relative error in the prediction is given in Equation 7, where \( y(x) \) is the actual value from CFD.
simulation and $\tilde{y}(x)$ is the predicted value using the metamodels. As it can be seen from Table 2, OAAO is performing much better in pressure drop prediction however AAO is better in predicting heat transfer coefficient. The main advantage in using OAAO as described earlier is the saving in the computational cost.

$$R_{Error} = \left| \frac{y(x) - \tilde{y}(x)}{y(x)} \right| \times 100\%$$

(7)

<table>
<thead>
<tr>
<th></th>
<th>$R_{Error}$ in h %</th>
<th>$R_{Error}$ in $\Delta P/L$ %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average</td>
<td>AAO</td>
<td>OAAO</td>
</tr>
<tr>
<td>Average</td>
<td>1.16</td>
<td>2.08</td>
</tr>
<tr>
<td>Maximum</td>
<td>6.12</td>
<td>4.56</td>
</tr>
<tr>
<td>Minimum</td>
<td>0.03</td>
<td>0.83</td>
</tr>
<tr>
<td>STD</td>
<td>1.31</td>
<td>1.15</td>
</tr>
</tbody>
</table>

STD : standard deviation

It can be seen from the results that OAAO is performing better while reducing significantly the computational cost, i.e., reducing the total number of CFD simulation required. These are the main advantages of using online approximation assisted optimization. However, offline approximation assisted optimization requires more samples to build a globally accurate metamodels which means more samples are wasted in the entire design space without affect the performance in the expected optimum region. Although the previous conclusion is true for a particular optimization problem, it is important as well to mention that offline approximation assisted optimization is more efficient if the globally accurate metamodels will be used later to optimize other products with different objectives based on the same design space. In this case, no more CFD simulations will be needed. On the other hand, using online approximation assisted optimization with new objectives requires more runs as a result of changing the expected optimum region.

6. CONCLUSIONS

Online and offline approximation assisted optimization approaches are used to obtain optimum plate heat exchanger designs based on single phase liquid. Kriging metamodels are built for both the heat transfer coefficient and for the pressure drop per unit length. These metamodels are used to predict the objectives and constraints within multi-objective genetic algorithm. In online approximation assisted optimization, the optimum solutions are filtered in both objective and design space in order to select best samples to update the metamodels. The samples are selected in the expected optimum region with a space-filling constraint to prevent clustering of samples in the design space. This procedure is iterative in nature and is carried out until a predefined stopping criterion is met. This online optimization approach predicted better optimum designs with high accuracy compared to offline approximation assisted optimization approach. The final results are verified using CFD simulations. The errors are small which indicates that the accuracy of the online approximation assisted optimization method is acceptable. The approximation technique resulted in a significant reduction in computational time compared to conventional optimization technique. Only 112 CFD simulations are required for building and updating the metamodels in online approximation assisted optimization compared with 200 samples required for offline approximation approach. Both offline and online approximation techniques are efficient when compared to several thousands of actual simulations required for conventional MOGA (~ 5100 simulations). The approaches presented in this paper are generic and can be applied for any heat exchanger or electronic cooling device optimization.
**NOMENCLATURE**

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>AAO</td>
<td>Offline Approximation Assisted Optimization</td>
</tr>
<tr>
<td>CFD</td>
<td>Computational Fluid Dynamics</td>
</tr>
<tr>
<td>DOE</td>
<td>Design of Experiments</td>
</tr>
<tr>
<td>MED</td>
<td>Maximum Entropy Design</td>
</tr>
<tr>
<td>MOGA</td>
<td>Multi-Objective Genetic Algorithm</td>
</tr>
<tr>
<td>OAAO</td>
<td>Online Approximation Assisted Optimization</td>
</tr>
<tr>
<td>PHX</td>
<td>Plate Heat Exchanger</td>
</tr>
<tr>
<td>PPCFD</td>
<td>Parallel Parameterized Computational Fluid Dynamics</td>
</tr>
<tr>
<td>RError</td>
<td>Relative Absolute Error</td>
</tr>
<tr>
<td>b</td>
<td>Corrugation depth (mm)</td>
</tr>
<tr>
<td>β</td>
<td>Corrugation angle (degree)</td>
</tr>
<tr>
<td>h</td>
<td>Heat Transfer Coefficient (W/m² K)</td>
</tr>
<tr>
<td>ΔP/L</td>
<td>Pressure drop per unit length (Pa/m)</td>
</tr>
<tr>
<td>u</td>
<td>Velocity (m/s)</td>
</tr>
<tr>
<td>p</td>
<td>Corrugation pitch (mm)</td>
</tr>
</tbody>
</table>

**REFERENCES**


ANSYS FLUENT 12.0 Documentation, ANSYS Inc., 2009.


