Applied Thermal Engineering 101 (2016) 576–591

Contents lists available at ScienceDirect

Applied Thermal Engineering

journal homepage: www.elsevier.com/locate/apthermeng

Research Paper

Heat transfer enhancement and optimization of flat-tube multilouvered fin compact heat exchangers with delta-winglet vortex generators

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HIGHLIGHTS

- Heat transfer enhancement about 21.27% for Re = 120 and 23.52% for Re = 240.
- Particular behavior of flow pattern and heat transfer characteristics.
- Optimized solutions are quite different for two types of geometries and Reynolds numbers.
- Arrangement of delta winglets is dependent on Reynolds number.

ARTICLE INFO

Article history:
Received 28 September 2015
Accepted 23 December 2015
Available online 4 January 2016

Keywords:
Heat transfer enhancement
Multi-louvered fin heat exchangers
Delta-winglet vortex generators
Compound heat transfer techniques
Artificial neural networks
Genetic algorithm

ABSTRACT

Surrogate-based optimization procedure is used to maximize the heat transfer of multilouvered fin compact heat exchangers with delta-winglet vortex generators (DWL). Five input parameters, such as louver angle and DWL angles of attack and positions, were chosen. The heat transfer enhancement performance of two distinct geometries, GEO_1 and GEO_2, with two rows of delta-winglets were considered on this research. Reynolds numbers of 120 and 240, based on hydraulic diameter, were investigated. The surrogate-based optimization procedure uses the NSGA-II (Non-Dominated Sorting Genetic Algorithm) combined with artificial neural networks. Compared with the respective baseline geometry (louvered fin without DWLs), the results showed that GEO_1 optimized solutions increased the heat transfer by 21.27% and 23.52% with associated pressure loss increase of 24.66% and 36.67% for the lower and the higher Reynolds numbers, respectively. For GEO_2 optimized solutions, the heat transfer was increased by 13.48% and 15.67% with an increase of the pressure drop by 20.33% and 23.70%, for the lower and the higher Reynolds numbers, respectively. The optimized solutions showed that heat transfer behind the second row of delta-winglets are as high as that behind the first row, for both Reynolds numbers. The flow patterns and heat transfer characteristics from optimized solutions presented some particular behavior, differently from the findings when louvered fin and DWLs are applied separately.

1. Introduction

The subject of heat transfer enhancement is of significant interest in developing compact heat exchangers to meet the need for high efficiency and low cost, which are as small as possible and as light as possible. The combination of multi-louvered fins and delta-winglet vortex generators has shown to be a promising strategy to enhance heat transfer in compact heat exchangers. Both louvered fins and vortex generators are recognized as enhancement techniques that have shown good results for heating, ventilation, air-conditioning and refrigeration applications.

The first attempt to the combination of louver fins and delta winglets vortex generators was a patent by Diemer-Lopes and Yanagihara [1] in which both enhancement techniques were applied to fin-tube heat exchangers for air-conditioning application. Dezan et al. [2] numerically investigated the combination of louver and delta-winglets applied to flat-tube compact heat exchangers. The screening analyses of the input parameters in terms of heat transfer and pressure drop indicated that there is no interaction between louver angle and DWL parameters. The authors also showed that the contribution of louver angle and delta-winglet parameters is strongly dependent of louver height, DWL frontal area and Reynolds number on heat transfer; instead, the louver angle is the most significant contributor to the friction factor. Huisseune et al. [3] studied the influence of the louver and delta winglet geometry on a round tube heat exchanger. The main conclusion was that small fin pitch and large louver angle cause strong deflection of the flow and then a

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http://dx.doi.org/10.1016/j.applthermaleng.2015.12.107
1359-4311/

great contribution of the louvers is observed. However, in this case, the generation of longitudinal vortices was suppressed and then the effect of DWL was small.

Sanders and Thole [4] studied the effects of winglets to augment tube wall heat transfer in louvered fin heat exchangers. Regarding Reynolds number of 230, none of the winglet arrangements produced augmentations greater than 4%. Augmentations at Reynolds numbers of 615 and 1016 were much higher than those ones at 230, and the best heat transfer enhancement was found with rectangular winglets giving 38%, 36% and 3% at Reynolds numbers of 1016, 615 and 230, respectively. Numerical and experimental investigations of heat transfer augmentation along the tube wall of a multilouvered fin by using delta winglet were made by Lawson and Thole [5]. The piercings disrupted the vortex formation by allowing flow pass through the piercings and following the louver-directed flow path. While piercings were shown to affect negatively the heat transfer performance along the tube wall relative to winglets placed on solid louvered fins, they have the desirable effect of lowering pressure losses.

Salviano et al. [6] proposed a thermal-hydraulic optimization procedure for DWL angles of attack and positions on thermal-hydraulic performance of plate-fin compact heat exchanger by using surrogate-based optimization and direct optimization. Direct optimization reported better results than surrogate-based optimization for all objective functions. Abdollahi and Shams [7] optimized shape and angle of attack of winglet vortex generator in a rectangular channel for heat transfer enhancement. A combination of CFD, artificial neural networks and non-sorting genetic algorithm were applied to the optimization process. Mishra et al. [8] proposed a genetic algorithm (GA) based optimization technique for crossflow plate-fin heat exchangers using offset-strip fins. Tan et al. [9] reported the use of artificial neural network (ANN) models to simulate the thermal performance of a compact fin-tube heat exchanger.

Xie et al. [10] used artificial neural network (ANN) to correlate experimentally the computed Nusselt numbers and friction factors of three kinds of fin-and-tube heat exchangers having plain fins, slit fins and fins with longitudinal delta-winglet vortex generators. Sanaye and Dehghandokht [11] proposed a modeling and multi-objective optimization of parallel flow condenser.

Hatami et al. [12] used a vortex generator heat exchanger to recover exergy from the exhaust of an OM314 diesel engine. Twenty delta-winglet vortex generators with angle of attack equal to 30° were used to increase the heat recovery. Results from optimization indicated that high engine loads and low water mass flow rates were more suitable from the second law view point to minimize the irreversibility and maximize the exergy recovery in the heat exchanger.

Hatami et al. [13] proposed a new design of heat exchanger to recover exergy from exhaust of a diesel engine. Twenty vortex generators with optimum dimensions and angle of attack were located in the exhaust to reach more exergy recovery. The authors showed that the proposed heat exchanger enhanced the heat recovery significantly. Also, exergy analysis confirmed that VGs can enhance exergy recovery more than 50% compared to previous simple designs.

In this research, the surrogate-based optimization (Artificial Neural Networks combined with Non-Dominated Sorting Genetic Algorithm) of heat transfer is used. The input variables for optimization procedure are louver angle, DWL angle of attack and DWL streamwise positions for two rows of DWLs. The heat transfer enhancement performance of two distinct geometries, GEO_1 and GEO_2, was evaluated. For GEO_1, the louver height is smaller than the louver height of the GEO_2 but with higher DWL frontal area than that of the GEO_2. Moreover, both geometries have the same total superficial area and hydraulic diameter. Latin Hypercube Sampling (LHS) is used as the method to generate random samples from some prior probability distribution on parameter space. This method is well known as a successful method applied to design computer experiments, especially when the dimension of the solution design space notably grows. Finally, there are no reports taking into account the heat transfer optimization of the independent input variables for two rows of DWLs by considering simultaneously their relationships with louver angle. Moreover, the flow characteristics and the heat transfer patterns of the optimized solutions as well as the interactions between longitudinal vortices and louver-directed flows are discussed.

1.1. Surrogate-based optimization

For any design and modeling purpose, the ultimate aim is to gain sufficient insight into the system of interest so as to provide more accurate predictions and better designs. As computing power has rapidly increased and made accessible, it is possible to model some of these processes with a sophisticated computer code. In the past decades, computer experiments or computer-based simulations have become topics in statistics and in engineering, receiving great attention from both practitioners and the academic community.

Currently, there are different DoE methods that can be classified into two categories: “classic” DoE methods and “modern” DoE methods. The classic DoE methods, such as full-factorial design, Central Composite Design (CCD), Box–Behnken and D-Optimal Design (DOD), were developed for laboratory experiments, aiming at reducing the effect of random error. In contrast, modern DoE methods such as Latin Hypercube Sampling (LHS), Orthogonal Array Design (OAD) and Uniform Design (UD) were developed for deterministic computer experiments without random error. An overview of the classic and modern DoE methods was presented by Giunta et al. [14]. LHS has long been used as an alternative to grids of computer experiments and is applied to the present work. Similarly to a regular grid, a LHS partitions each parameter range into equally spaced values.

Artificial Neural Networks (ANN) using back propagation method was chosen as the surrogate model. In this method, weight values are adjusted in an iterative fashion while moving along the error surface to arrive at a minimal range error, when inputs are presented to the network to learn the pattern of the data.

1.1.1. Artificial neural network (ANN)

Artificial neural network (ANN) plays an important role in predicting the output of linear and non-linear problems in different fields of research. The term neural network has evolved to encompass a large class of models and “learning” (i.e., parameter estimation) methods [15].

Generally, a neural network means a network of many simple processors (units) operating in parallel. Each processor has a small amount of local memory. The units are connected by communication channels (connections), which usually carry numeric data, encoded by one of various ways. One of the best-known examples of a biological neural network is the human brain. It has the most complex and the most powerful structure, which, by learning and training, controls human behavior toward responding to any problem encountered in everyday life.

A multilayer-perceptron (MLP; Fig. 1) that consists of input, hidden and output layers with nonlinear and linear activation functions in the hidden and output layers, respectively, approximates inputs and outputs as follows:

$$\hat{y} = \sum_{j=1}^{d} \beta_j b_j(v_j) + \beta_0 \quad (1)$$

where d is a pre-specified integer, β_j is the weight connection between the output and the *jth* component in the hidden layer, and $b_j(v_j)$ is the output of the *jth* unity in the hidden layer,