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Using Neural Network and Genetic Algorithm for Modeling and Multi-objective Optimal Heat Exchange through a Tube Bank

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ABSTRACT

In this study, by using a multi-objective optimization technique, the optimal design points of forced convective heat transfer in tubular arrangements were predicted upon the size, pitch and geometric configurations of a tube bank to gain to wide range of design point candidates, and a novel multi-objective and variable prediction model. In this way, the main concern of the study is focused on calculating the most favorable geometric characters which may gain to a maximum heat exchange as well as a minimum pressure loss. Gathering the required wide range of set of design information, a numerical simulation of various configurations of the elliptic tubular arrangements was performed using the FLUENT software. Afterwards, the group method of data handling (GMDH)-type neural network and the evolutionary algorithm (EAs) were used to model the effects of design parameters, i.e. horizontal diameter of ellipse (a), vertical diameter of ellipse (b), transverse pitch (S_n), and longitudinal pitch (S_p) on pressure loss (ΔP) and the temperature difference (ΔT) to achieve a meta- model through a prediction procedure using evolved GMDH neural network. Finally, the model was used to gain the multi-objective Pareto-curves to depict the optimal design zones.

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1. INTRODUCTION

Designing optimal shapes for practical engineering applications has been the subject of numerous publications during the last decade [1-4]. A variety of optimization methods can be found in the literature, based on different strategies. In the current work, the multi-objective optimization problem is the main concern, since it covers many interesting application fields. As a matter of fact, most times, engineers responsible for design of industrial devices have to face problems with more than one objective to be fulfilled at the same time. Moreover, the objectives of the optimization process are often concurrent (a simple example is the quality/price trade-off).

In a tube bank heat exchanger optimization problem consists of finding the best geometry of the tubes to increase heat exchange as well as minimizing the pressure loss. The two corresponding numerical parameters are average temperature difference (ΔT) and the pressure loss (ΔP). These two objectives are obviously inter-related. If the exchange surface increase, the heat exchange will be favored and the temperature difference between the inflow and outflow enhances. However, simultaneously, this may cause higher pressure loss at the same mass flow rate.

System identification and modeling of complex processes using input-output data have always attracted many research efforts. In fact, system identification techniques are applied in many fields in order to model and predict the behavior of unknown and/or very complex systems based on given input-output data ([5],[6],[7],[8],[9]).

The authors previously examined the mentioned method in micro-channel optimal design [10], in aero-dynamic control of stall inception over an airfoil [11], and aero-thermodynamic optimal design of turbo- prop engines [12].

Optimal designs in engineering cases has always a great role to achieve robust systems. The techniques used to gain to an optimal design in multi-component system has played the main role of optimization. Among these techniques, the single and the multi objective methods has been introduced in [13], [14] and

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[15]. These studies may conclude that the advantage of evolutionary algorithms is very fruitful to solve many real-world optimal design or decision making problems which are indeed multi-objective. The evolutionary algorithms showed that there are a set of optimal points that may chosen and the pareto fronts may give the limits of such sets ([16], [17]).

In this paper, GMDH-Type neural networks are first used to determine the effects of tube's sizes and pitches on both temperature difference (ΔT) and pressure loss (ΔP) in different configurations. The total number of data resulted from simulation are 80 from which 65 are used for training whilst the remaining 15 data in merely used for model evaluation. The obtained polynomial neural models are then used in a Pareto-based optimization approach to find the best possible combination of temperature difference (ΔT) and pressure loss (ΔP) known as the Pareto front. The corresponding variations of design variables, namely, horizontal diameter of ellipse (a), vertical diameter of ellipse (b), transverse pitch (S_n) and longitudinal pitch (S_p) known as Pareto set constitute some important design principles which can be effectively used for optimal design of tube bank heat exchanger.

2. MODELING

As it was mentioned before, the GMDH-type neural networks are used for medelling. As it was reported by N. Narimanzadeh et al. [8], the literature gives that a wide range of evolutionary design methods even in architectures or connection weights of neural networks separately.

3. SIMULATION

As a thermal engineering application by coupling Genetic Algorithms and CFD codes, a two-dimensional model of an ellipse sectional tube bank heat exchanger is considered here. The simulated staggered configuration is shown in Figure 1 and in-line configuration is shown in Figure 3. Computing the flow as a steady two-dimensional flow is in this case a very acceptable approximation of the true physics, as the tube length in the *z* direction is very large compared to its width.

Air with constant flow rate $\dot{m} = 0.5\,kg/s$ enters the domain at $T_{inlet} = 293k$ and warmed up by passing through the tubes in which a hot fluid flows in the corresponding practical application. The tubes are supposed to have a constant outer wall temperature, $T_{wall} = 333k$. The outlet is at atmospheric pressure.

By using circular tube bank tables to obtain acceptable geometry for elliptic tube bank:

$10 \le a \le 25$ *mm a: horizontal diameter of ellipse*
$10 \le b \le 25$ *mm b: vertical diameter of ellipse*
$30 \le S_p \le 50$ *mm S_p: longitudinal pitch*
$30 \le S_n \le 50$ *mm S_n: transverse pitch*

80 states design variables is defined using Hammersely Sequence Sampling for simulation and profile contour (tubes) from design variables is generated.

For the different simulations, the boundary conditions are the same, only the computational geometries differ. After defining the computational geometry and obtaining a corresponding mesh, the numerical simulation can be performed. The two-dimensional fields of pressure and temperature are obtained in this way.

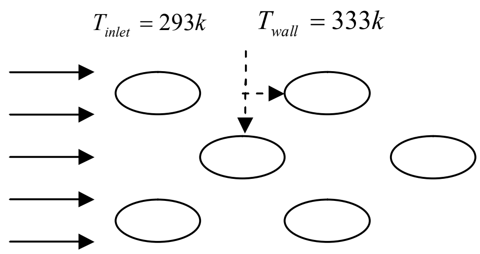

Figure 1. Schematic description of the tube bank heat exchanger at an staggered configuration.

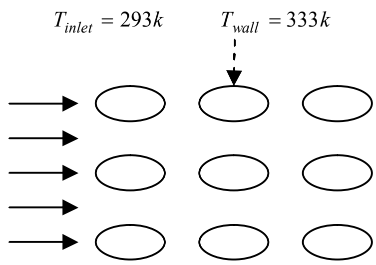

Figure 2. Schematic description of the tube bank heat exchanger at an in-line configuration.

4. EVALUATION OF THE OBJECTIVES

In present case, the evaluation of an individual set of parameters requires four steps:

(1) The generation of the profile contour from the design variables;
(2) The generation of an appropriate mesh for the obtained geometry;
(3) The CFD simulation, the solution of the governing coupled equations for the flow variable and the energy on the mesh generated in the previous step;
(4) The post-processing of the obtained results to extract the values of the objective functions for these specific design variables.

After having defined the geometry, the mesh is produced in an automatic manner by GAMBIT software. The internal fluid region is meshed using triangular cell elements using the "pave" algorithm. This automatic mesh generation has worked in many cases without effective errors. The adequate mesh has been obtained on a grid dependence study which is not preferred to be presented here with some other details on CFD approaches.

The discretized governing equations are solved iteratively in a segregated manner using a finite-volume description by FLUENT solver. To improve the accuracy of second-order discretization is systemically used for all variables, along with a double-precision computation. The normalized residuals are computed for all the iterations. As soon as all of these residuals fall below a prescribed value, convergence is reached. In our case, the fixed prescribed value is 10^4 for the flow equations and 10^6 for the temperature equation, providing a sufficient accuracy for an acceptable time.

The mass flow-pressure coupling is treated with the standard SIMPLEC method. In most cases, the convergence is achieved in 500-700 iteration steps.

The inlet (left side in Figures 1 and 2) boundary is considered as a mass flow inlet with imposed conditions for flow rate, set to $\dot{m} = 0.5\,kg/s$, and temperature $T_{inlet} = 293k$. Wall boundary conditions with constant temperature $T_{wall} = 333k$ are prescribed on all tubes. Periodic conditions are applied in between the tubes on the top and bottom. On the right, a pressure outlet condition relaxing to the atmospheric pressure is imposed.

After convergence, the temperature difference between the inlet (uniform constant value) and averaged value along the outlet is computed as well as the pressure loss to provide the two objective parameters. The computed temperature and pressure fields from one of the optimum solutions are presented as a sample in Figures 3 – 6.

5. MODELLING OF TEMPERATURE DIFFERENCE AND PRESSURE LOSS

The input-output data sets used in such modeling involve two different data tables obtained from simulation. The first table consists of four variables as inputs namely, horizontal diameter of ellipse (a), vertical diameter of ellipse (b), transverse pitch (S_n), longitudinal pitch (S_p) and one output which is pressure loss (ΔP). The second table consists of the same four variables as inputs and another output which is temperature difference (ΔT). These tables consist of the total 80 pattern numbers which have been obtained from the simulation to train such GMDH-type neural networks. However, in order to demonstrate the prediction ability of evolved GMDH-type neural networks, the data has been divided into two different sets, namely, training and testing sets.

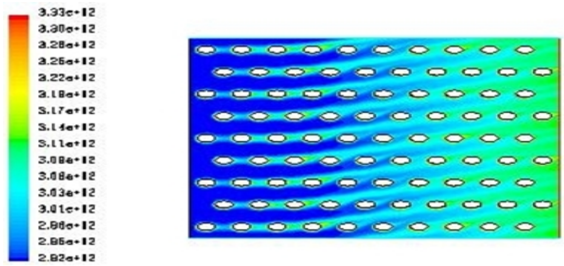

Figure 3. A sample temperature field in Kelvin, for one of the optimum solutions, at staggered configuration.

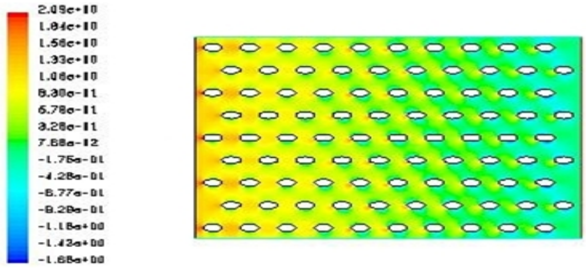

Figure 4. A sample pressure field in Pascal for one of the optimum solutions at staggered configuration (same solution as Figure 4).

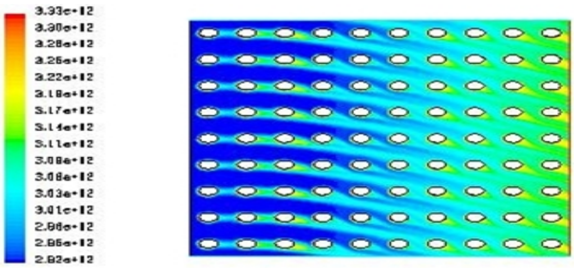

Figure 5. A sample temperature field in Kelvin, for one of the optimum solutions, at in-line configuration.

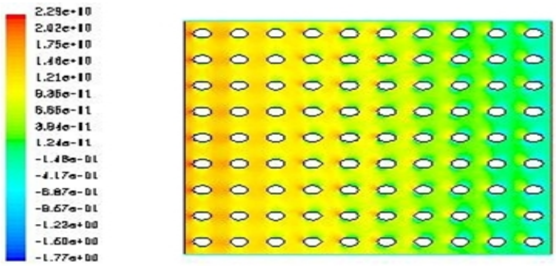

Figure 6. A sample computed pressure field in Pascal for one of the optimum solutions at in-line configuration (same solution as Figure 6).

The training set, which consists of 65 out of 80 inputs-output data pairs, is used for training the neural network models using the evolutionary method of this paper. The testing set, which consists of 15 unforeseen inputs-output data samples during the training process, is merely used for testing to show the prediction ability of such evolved GMDH-type neural network models during the training process.

The very good behavior of such GMDH-type neural network models are also depicted in Figures 7 -10 for training data and testing data of both pressure loss and temperature difference, at staggered and in-line configuration respectively.

It is clearly evident that the evolved GMDH-type neural network in terms of simple polynomial equations can successfully model and predict the output of testing data that has not been used during the training process.

The models obtained in this section can now be utilized for a Pareto multi-objective optimization of tube bank heat exchanger considering pressure loss (ΔP) and temperature difference (ΔT) as conflicting objectives. Such study may unveil some interesting and important optimal design principles that would not have been obtained without the use of a multi-objective optimization approach.

6. MULTI-OBJECTIVE OPTIMIZATION

The Multi objective optimization techniques and its details such as the mathematical relations, the definition of the pareto characteristics and their basis are the same asmetioned in previous works [18] and [19].

This is necessary to highlight that as it was metioned in [19], using the Evolutionary algorithms with their parrallel os population-based search character highly may reduce the deficiencies which may be face in classical methods.

7. PARETO OPTIMIZATION OF THE TUBE BANK USING POLYNOMIAL NEURAL NETWORK MODELS

In order to investigate the optimal performance of the tube bank in different conditions of size, pitch and configuration, the polynomial neural network models obtained in previous sections are now deployed in a multi-objective optimization procedure. The two conflicting objectives in this study are pressure loss (ΔP) and temperature difference (ΔT) to be simultaneously optimized with respect to the design variables, ,namely, horizontal diameter of ellipse (a), vertical diameter of ellipse (b), transverse pitch (S_n), longitudinal pitch (S_p). Evidently, it can be observed that the temperature difference (ΔT) is maximized whilst pressure loss (ΔP) is minimized in the set of objective functions (ΔT, ΔP).

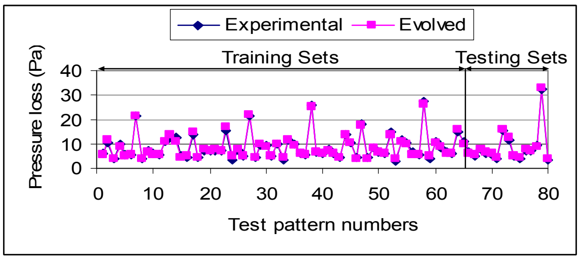

Figure 7. Comparison of simulation values of pressure loss with the predicted values using evolved GMDH neural networks at staggered configuration

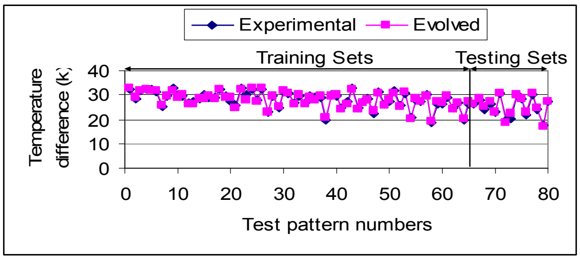

Figure 8. Comparison of simulation values of temperature difference with the predicted values using evolved GMDH neural networks at staggered configuration.

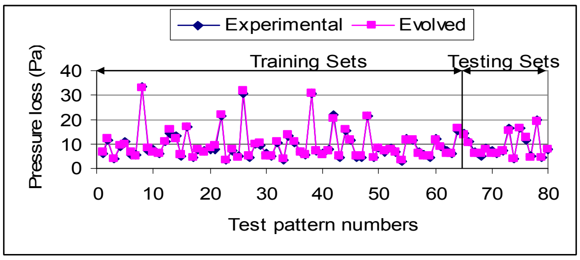

Figure 9. Comparison of simulation values of pressure loss with the predicted values using evolved GMDH neural networks at in-line configuration.

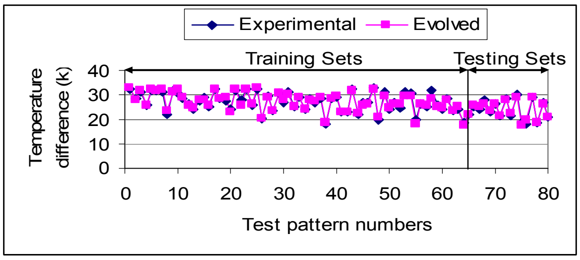

Figure 10. Comparison of simulation values of temperature difference with the predicted values using evolved GMDH neural networks at in-line configuration.

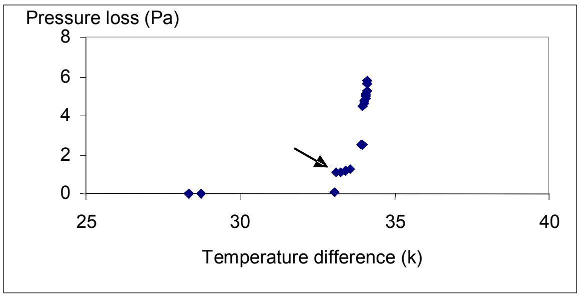

Figure 11. Optimal Pareto front of conflicting objective functions pressure loss (ΔP) and temperature difference (ΔT) at staggered configuration.

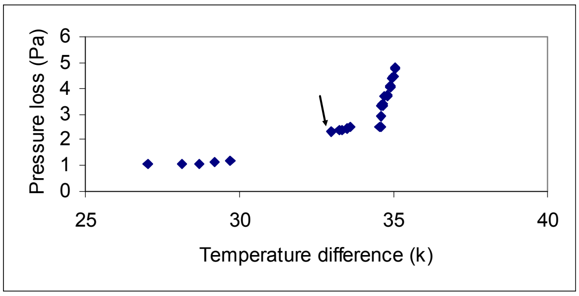

Figure 12. Optimal Pareto front of conflicting objective functions pressure loss (ΔP) and temperature difference (ΔT) at in-line configuration.

The corresponding Pareto front of two objectives (ΔT) and (ΔP) at staggered and in-line configuration has been shown in Figures 11 and 12, using the hybridized approach.

It is clear from these figures that choosing appropriate value for horizontal diameter of ellipse (a), vertical diameter of ellipse (b), transverse pitch (S_n), longitudinal pitch (S_p), to obtain a better value of one objective would cause a worse value of another objective. However, if the set of decision variables is selected based on each of the Pareto set, it will lead to the best possible combination of those two objectives. In other words, if any other decision variables (a), (b), (S_n) and (S_p) is chosen, the corresponding values of the pair of objectives, (ΔP) and (ΔT), will locate a point inferior to the Pareto front.

Clearly, there are some important optimal design facts between the two objective functions which have been discovered by the Pareto optimization of the polynomial neural network models using data resulted from simulation of the tube bank heat exchanger. Such important design facts could not have been found without the multi-objective Pareto optimization of those polynomial models. From Figures 11 to 12, two sections can be seen which demonstrate these important optimal design facts. First section exhibits increase of temperature difference (ΔT) whilst pressure loss (ΔP) is nearly constant. Second section exhibits a significant increment of pressure loss (ΔP) with a small change in temperature difference (ΔT). Therefore, changing the horizontal diameter of ellipse (a), vertical diameter of ellipse (b), transverse pitch (S_n), longitudinal pitch (S_p), in conjunction with configuration as decision variables should be in such a way that the operating condition of the heat exchanger in terms of temperature difference (ΔT) and pressure loss (ΔP) lies between this two sections (marked section) of the Pareto optimal front. This will not only ensure the optimal behavior of the heat exchanger but also prohibit such deficiency involved in those two sections.

8. CONCLUSION

In this paper, a meta model have been found by evolved Gs-GMDH type neural networks using input-output data obtained from simulation. The derived polynomial models have been used in an evolutionary multi-objective Pareto based optimization process so that some interesting and informative optimum design aspects have been revealed for the tube bank heat exchanger. The combined application of GMDH neural network modeling of input-output data resulted from simulation and subsequent Pareto optimization process could highly improve the efficiency and the required assurance of having multiple optimal designs.

As the main conclusions, the modeling and the multi- objective optimization technique provided a novel tool for heat exchanger designers as well as a wide range of optimum design zone.

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چکیده

در مقاله حاضر با استفاده ازروش بهینه‌سازی چند هدفی، نقاط بهینه طراحی انتقال حرارت اجباری در یک دسته لوله بر اساس سایز، گام و دیگر ویژگی‌هایی هندسی پیش بینی شده است. در این ارتباط تمرکز کار بر محاسبه ویژگی‌های هندسی است منجر به بیشترین تبادل حرارتی و حداقل افت فشار می‌گردد. به منظور حصول داده‌های لازم برای مدلسازی و طراحی بهینه از نرم افزار فلوئنت برای شبیه‌سازی و حل معادلات جریان استفاده شده است. پس از این بخش، روش گروه‌بندی داده‌های GMDH به‌عنوان نوعی از مدل‌سازی شبکه عصبی به‌همراه الگوریتم تکاملی برای حصول به یک مدل چند متغیره مورد استفاده قرار گرفته است و پارامترهای قطر افقی بیضی، قطر عمودی بیضی، گام‌های عرضی و طولی به‌عنوان متغیر برای توابع هدف افت فشار و اختلاف دما مورد استفاده قرار گرفته است. برای این امر ابتدا پیش‌بینی‌های مدل براساس داده‌ای موجود ارزیابی و سپس با استفاده ار داده‌های مدل موجود منحنی‌های پرتو طراحی بهینه ارایه شده است.

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