Optimization and design of cooling systems using a hybrid neural network and genetic algorithm methodology

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Abstract

In this paper a novel method for the design and optimization of cooling systems is presented. The numerical solution of free convection from a heated horizontal cylinder confined between adiabatic walls obtained from a finite element solver is used to propose a non-linear heat transfer model of GMDH type approach. In the context of GMDH model, three different methods depending on the structure of neural network are implemented. The system of orthogonal equations is solved using a SVD scheme. The coefficients of second order polynomials are computed and their behavior is discussed. In addition, to demonstrate the performance of the predicted model, the numerical data are divided into trained and prediction data, respectively. The model is based on trained data and it is validated using the prediction data. In the next step, using the above-mentioned model and the genetic algorithms, the optimum coefficient of heat transfer is obtained. The results reveal the robustness and excellent performance of the hybrid procedure introduced in this paper.
Keywords: GMDH, GA, neural network, cooling systems.

1 Introduction

Design of efficient cooling systems for electronic industry has been one of the major challenges of the past 20 years. The main issue is the amount of heat that can be transferred from the electronic units to the surrounding such that the unit performs in its best design conditions. Indeed, the engineer is confronted to the non-trivial problem of finding the least geometrical space without jeopardizing the maximum working temperature limit of elements of the electronic system.

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Nowadays, different methods of analysis and prediction based on standard numerical methods such as CFD and FEM research on commercial packages are employed. Experimental approaches being complex and expensive have also been considered as alternative research tools [1-4]. In this paper, a novel method of prediction and optimization is presented. Modeling of processes and system identification using input-output data has 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]. Theoretically, in order to model a system, it is required to understand the explicit mathematical input-output relationship precisely. Such explicit mathematical modeling is, however, very difficult and is not readily tractable in poorly understood systems. Alternatively, soft-computing methods [6], which concern computation in imprecise environment, have gained significant attention. The main components of soft computing, namely, fuzzy-logic, neural network and genetic algorithm, have shown great ability in solving complex non-linear system identification and control problems. Several research efforts have been expended to use evolutionary methods as effective tools for system identification [7-9]. Among these methodologies, the Group Method of Data Handling (GMDH) algorithm is a self-organizing approach by which gradually more complicated models are generated, based on the evaluation of their performance on a set of multi-input-single-output data pairs (x_i , y_i) ($i=1,2,\ldots,M$). The GMDH was first developed by Ivakhnenko [10] as a multivariate analysis method for complex systems modeling and identification. In this way, GMDH was used to circumvent the difficulty of knowing a priori knowledge of a mathematical model of the process being considered. In other words, GMDH can be used to model complex systems without having specific knowledge of the systems. The main idea of GMDH is to build an analytical function in a feed forward network based on a quadratic node transfer function [11] whose coefficients are obtained using a regression technique. In recent years, the use of such self-organizing network leads to successful application of the GMDH-type algorithm in a broad range area in engineering, science and economics [11-14].

In this paper, it is shown that GMDH-type neural network can effectively model and predict the heat transfer, each as a function of important input parameters in free convection from a horizontal cylinder confined between adiabatic walls. In this way, three different simple heuristic methods for designing such networks are proposed and their performances are enhanced using singular value decomposition (SVD). In the next step, using the above-mentioned model and the genetic algorithms, the optimum configuration for maximum coefficient of heat transfer is obtained.

2 Modeling using GMDH-type networks

Three different approaches for structural identification of GMDH-type networks are presented as follows.

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Method I: increasing-selection-pressure approach
In this approach, only one parameter called selection pressure is sequentially increased in different layers in order to determine the number of neurons in each layer as well as the number of layers in network. The main steps of this approach are described as follows.

Step 1. Consider $N_1 = n$ neurons in the first layer from the vector of input variables $\text{Vec. of Var.} = \{x_1, x_2, x_3, ..., x_m\}$, where n is the number of input. Set k=1; Set selection pressure $SP_k = 1$.

Step 2. Construct $N_k(N_k - 1)/2$ neurons according to all possibilities of connection by each pair of neurons in the layer. This can be achieved by forming the quadratic expression $G(x_i, x_j)$ which approximates the output y in

$$\hat{y} = G(x_i, x_j) = a_0 + a_1 x_i + a_2 x_j + a_3 x_i x_j + a_4 x_i^2 + a_5 x_j^2 \tag{1}$$

with least-squares errors of equation

$$r^2 = \frac{\sum_{i=1}^{M} (y_i - G_i())^2}{\sum_{i=1}^{M} y_i^2} \rightarrow \min \ . \tag{2}$$

either by solving the normal equation

$$a = (A^T A)^{-1} A^T Y \tag{3}$$

or by SVD approach equation

$$a = V.\left[diag(\frac{1}{w_j}) \right].U^T.Y \tag{4}$$

Step 3. Set $SP_k = SP_{k-1} - 0.1$ (increase the selection-pressure) and select m_k neurons whose errors according to equation (2) are less than a certain value calculated from

$$\bar{r}^2 = SP_k \left(\frac{\sum_{j=1}^{v} r_j^2}{v} \right)$$

where

$$v = INT\left(SP_k \frac{N_k(N_k - 1)}{2} \right)$$

Step 4. Set $k = k + 1$ and $N_k = m_{k-1}$. If $(N_k \neq 1)$ Then go to Step 2. Otherwise END.

It should be noted that choosing the selection pressure according to step 3 is an important decision and can have a significant influence on the structure of the network.

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Method II: pre-specified-network approach
In this approach, number of layers in the network is per-specified as well as number of neurons in each of these layers. The main steps of this approach are described as follows.

Step 1. Consider $N_1 = n$ neurons in the first layer from the vector of input variables $Vec-of-\mathrm{var}=\{x_1,x_2,x_3,\ldots,x_n\}$, where n is the number of inputs. Set k =1 and $Number-of-layers = N_1$.
Step 2. Construct

$$N'_k = \frac{N_k(N_k-1)}{2}$$

Neurons according to all possibilities of connection by each pair of neurons in the layer. This can be achieved by forming the quadratic expression $G(x_i, x_j)$ which approximates the output y in equation (1) with least-squares errors of equation (2) either by solving the normal equation (3) or by SVD approach equation (4).

Step 3. Select the best pre-specified N_{k+1} neurons out of these N'_k neurons according to their values of r^2.
Step 4. If $(k+1 \neq N_1)$ Then Set $k = k+1$; $N_k = N_{k-1}$; go to 2. Otherwise END.

It should be noted that only one neuron is selected in the last layer.

Method III: error-driven approach
In this approach, the numbers of layers as well as the number of neurons in each layer are determined according to a threshold for error equation (2). In addition, unlike two previous approaches, some of input variables or generated neurons in different layers can be included in subsequent layers. It is, therefore, evident that the structure of such network may be more complicated than those generated in previous methods. The main steps of this approach are described as follows.
Step 1. Set K = 1; Set Threshold.
Step 2. Construct

$$N'_k = \frac{N_k(N_k-1)}{2}$$

Neurons according to all possibilities of connection by each pair of neurons in the layer. This can be achieved by forming the quadratic expression $G(x_i, x_j)$ which approximates the output y in equation (1) with least-squares errors of equation (2) either by solving the normal equation (3) or by SVD approach equation (4).
Step 3. Select the single best neuron out of these N'_k neurons, x' according to its value of r^2.
If (Error<Threshold) Then END; Otherwise Set $Vec-of-Var=\{x_1,x_2,x_3,\ldots.,x_n\}$.
Step 4. Set $N_k = N_k + 1$; go to 2.

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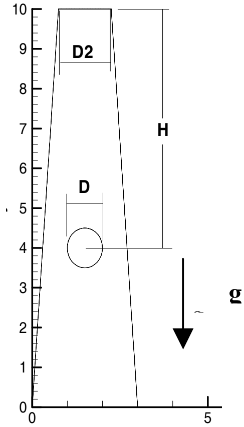

Figure 1: Free convection from a heated horizontal cylinder confined between adiabatic walls.

Table1: Root mean squares of errors.

Method	MSE	No. Layer	No. Neuron
I	0.011203	3	6
	0.010301	5	12
	0.010152	6	15
	0.00998	7	18
II	0.011203	3	6
	0.010422	4	9
	0.010301	5	12
	0.010152	6	15
III	0.009931	5	5
	0.008995	11	11
	0.007264	15	15
	0.003456	16	16
	0.002687	18	18
	0.001876	22	22

3 GMDH-type neural network modeling and prediction of heat transfer

Three methods discussed above are used to design GMDH-type network systems for a set of numerical solution of free convection from a heated horizontal cylinder confined between adiabatic walls (see Fig.1). The input data is obtained from a finite element solver reported in [15]. The selected parameters of interest

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which affect this multi-input-single-output system are h/D, D2, Ra, respectively, where:

$$Ra = \frac{\rho^2 g \beta D^3 \Delta T}{\mu^2}$$

In order to model these three-input-single-output set of data, each of the three methods previously mentioned was used separately in conjunction with SVD approach for the coefficient of the quadratic polynomials. The result shows that SVD approach for finding the quadratic polynomial coefficients is superior to direct solving of normal equations in most cases. Table 1 demonstrates such comparison of root mean squares errors (for heat transfer) using SVD by methods I, II and III. Accordingly figures 2 and 3 show the behavior of heat transfer, respectively, using GMDH-type network model constructed by method III in conjunction with SVD approach for the coefficients of quadratic polynomials. The structures of GMDH-type network for such three-input-single-output heat transfer process which have been obtained by method II and III are depicted in figures 4 and 5.

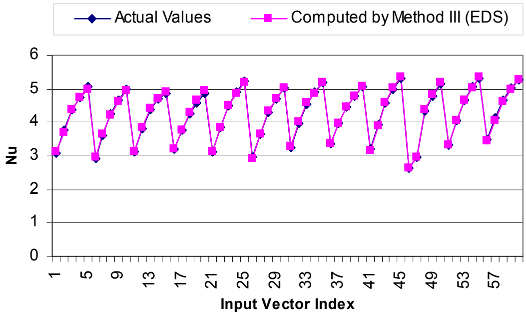

Figure 2: Variation of heat transfer coefficient with input data samples: Comparison of numerical solution with computed values (Method III).

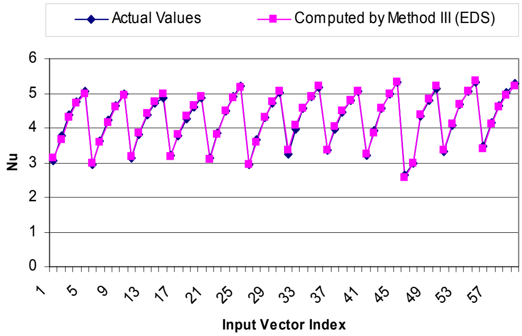

Figure 3: Variation of heat transfer coefficient with input data samples: Comparison of numerical solution with computed values (Method III).

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In order to demonstrate the prediction ability of such GMDH-type neural networks, the data have been divided into two different sets, namely, training and testing sets. The training set, which consists of 50 out of 60 input-output data, is used for training the GMDH-type neural network models using the three methods in conjunction with SVD approach for the coefficients of the quadratic polynomials. The testing set, which consist of ten unforeseen input-output data samples during the training process. In this way, table 2 demonstrates such comparison of root mean squares of errors (for heat transfer) using SVD by methods I, II and III. Accordingly, figure 6 and 7 show the modeling and prediction behavior of the corrected heat transfer coefficient parameters,

$$Nu = \frac{h\,D}{k}$$

(h = coefficient of convection heat transfer, D = diameter, k = coefficient of conduction heat transfer, Nu = Nusselt Number) respectively using GMDH-type network model constructed by method III in conjunction SVD approach for the coefficient of the quadratic polynomials.

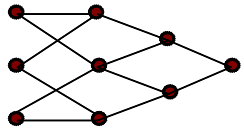

Figure 4: GMDH-type network obtained by method II.

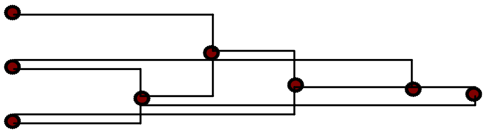

Figure 5: GMDH-type network obtained by method III.

Table 3: Root mean squares of errors (modeling and prediction).

Method	MSE(Model)	MSE(Prediction)	No. Layer	No. Neuron
II	0.014974	0.0069	2	3
	0.014974	0.773007	2	4
III	0.14974	0.003777	2	2
	0.012611	0.003001	3	3
	0.012063	0.002439	4	4
	0.0115	0.002443	5	5
	0.010826	0.002955	8	8
	0.009807	0.009784	11	11

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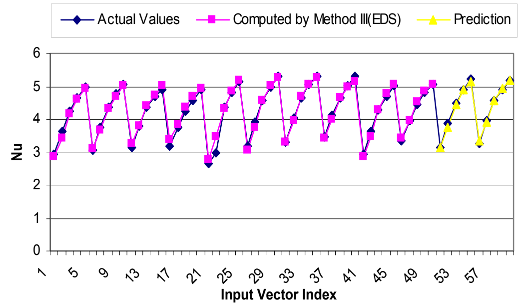

Figure 6: Variation of heat transfer coefficient with input data samples: Comparison of numerical solution with computed/predicted values (Method III).

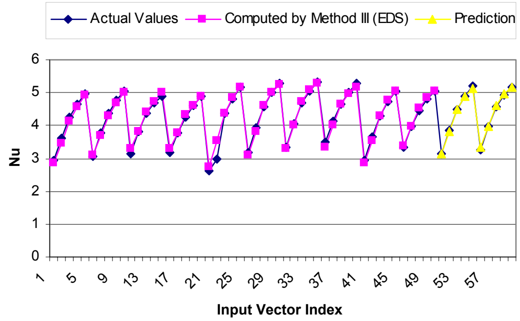

Figure 7: Variation of heat transfer coefficient with input data samples: Comparison of numerical solution with computed/predicted values (Method III).

It is evident that the performance of method III in the GMDH-type neural network modeling of corrected heat transfer coefficient parameters in heat transfer process of free convection from a heated horizontal cylinder confined between adiabatic walls in most cases in superior to those of both methods I and II.

4 Search for optimum heat transfer coefficient employing GA

Genetic algorithms are so called since they are modeled loosely upon the biological process of natural selection. They form successive populations of individual solutions to the problem. The algorithm attempts to improve the quality (referred to as "fitness" in the genetic algorithms context) of these individuals from generation to generation. The change in the population is achieved by the selection, reproduction and mutation procedures within the method. The operation of these three procedures is dependent upon the fitness of the individuals concerned.

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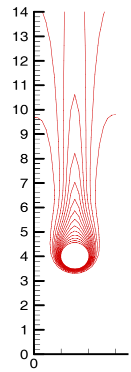

Figure 8: Isothermal lines around cylinder for H/D=10 and Ra=10^3 obtained employing the novel hybrid method.

Genetic algorithms are characterized by the fact that all the information for any individual in the population is encoded using some linear encoding system. This (usually binary) encoding is intended to be somewhat analogous to natural DNA consisting of a string of four kinds of chromosomes.

The standard encoding technique for applying genetic algorithms to non-linear optimization problems (where the parameters are continuous and real) is a concatenation of all the binary approximations to each number.

Having arrived at a consistent reversible encoding method and knowing that the initial population is randomly chosen, what remains is how to perform the changes from one "generation" to the next. It is achieved by a combination of three procedures, crossover, selection and mutation [16, 17].

In this stage, in order to find the optimum heat transfer coefficient from the obtained equations, EDS method with 18 layers and 18 neurons was used. Cost function and optimization constraints are as follows:

$$\text{Max. Nu} = f\,(h/D,\ D_2,\ Ra)$$
$$6 \le h/D \le 14$$
$$1 \le D_2 \le 3$$
$$1000 \le Ra \le 10000$$

It should be noted that in algorithm of finding the maximum of heat transfer coefficient, in addition to crossover, mutation, and selection operators, elitism operator is also employed.

Initial population was assumed to be 50 chromosomes with 15 Genes. Procedure of finding maximum was repeated for 100 generations, while probabilities of mutation and crossover were 0.005 and 0.6 respectively.

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Improvement of Genetic algorithm in finding the maximum of Nu function can be observed in figures 9. The solutions are as follows:

h/D = 1.2452e+001
D_2 = 1.9677e+000
Ra = 1.0000e+004
Nu = 5.8980e+000

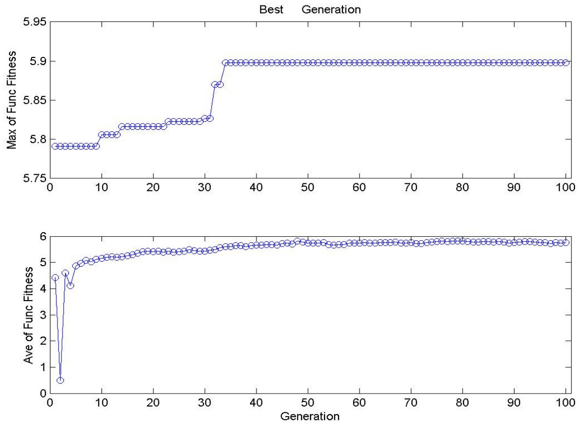

Figure 9: The optimum coefficient of heat transfer obtained by Genetic Algorithm ($6 \le h/D \le 14$, $1 \le D_2 \le 3$, $1000 \le Ra \le 10000$).

5 Conclusion

Three methods for designing GMDH-type networks have been proposed and successfully used for the modeling and prediction of the process parameters of the very complex process of heat transfer. In this way, it has been shown that GMDH-type networks provide effective means to model and predict heat transfer coefficient percentage according to different inputs. Moreover, it has been shown that SVD can effectively improve the performance of such GMDH-type networks over the traditional use of normal equations which can be constructed by each of the three methods. Such an application led to much simpler GMDH-type neural networks for which the set of the obtained polynomials representing the corrected heat transfer coefficient as functions of respective input variables have also been presented. In addition, the genetic algorithm is used to obtain the maximum heat transfer coefficient. The results reveal the robustness and excellent performance of the hybrid procedure.

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