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Modeling and Multi-Objective Optimization of Forward-Curved Blades Centrifugal Fans using CFD and Neural Networks

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Abstract

Increasing of head rise (H_R) and decreasing of head loss (H_L), simultaneously, are important purpose in the design of different types of fans. Therefore, multi-objective optimization process is more applicable for the design of such turbo machines. In the present study, multi-objective optimization of Forward-Curved (FC) blades centrifugal fans is performed at three steps. At the first step, Head rise (H_R) and the Head loss (H_L) in a set of FC centrifugal fan is numerically investigated using commercial software NUMECA. Two meta-models based on the evolved group method of data handling (GMDH) type neural networks are obtained, at the second step, for modeling of H_R and H_L with respect to geometrical design variables. Finally, using obtained polynomial neural networks, multi-objective genetic algorithms are used for Pareto based optimization of FC centrifugal fans considering two conflicting objectives, H_R and H_L. It is shown that some interesting and important relationships as useful optimal design principles involved in the performance of FC fans can be discovered by Pareto based multi-objective optimization of the obtained polynomial meta-models representing their H_R and H_L characteristics. Such important optimal principles would not have been obtained without the use of both GMDH type neural network modeling and the Pareto optimization approach.

Keywords: Forward-Curved Blades Centrifugal Fan; Multi-objective optimization; CFD; GMDH; Genetic Algorithms.

1. Introduction

The optimization of centrifugal fans is a special task in turbo machinery engineering, which has received considerable attention over the past decades. Lu et al. [1] numerically investigated the internal flow field of centrifugal fans. They could decrease the head loss and increase the total pressure using splitter blades in centrifugal fans. Sugimura et al. [2] investigated a multi-objective optimization process on centrifugal fans using multi-objective robust design exploration method (MORDE). They tried to determine the design variables which have the minimum turbulent noise level and the maximum efficiency. Forward-Curved (FC) blades centrifugal fans or squirrel cage fans are the one of the prime group of the centrifugal fans, which is used industrially in large scales. Kim and Seo [3] presented a response surface method using three dimensional Navier-Stokes analyses to optimize the shape of a forward-curved blades centrifugal fan and finally improved the efficiency of fan.

Head rise and head loss are important and independent objective functions in the design of FC fans, which can be used in a multi-objective optimization process. These objective functions are either obtained from experiments or computed using very timely and high-cost computer fluid dynamic (CFD) approaches, which cannot be used in an iterative optimization task unless a simple but effective meta-model is constructed over the response surface from the numerical or experimental data. Therefore, modeling and optimization of the parameters is investigated in the present study, by using GMDH-type neural networks and multi-objective genetic algorithms in order to maximize the head rise and minimize the head loss.

System identification and modeling of complex processes using input-output data have always attracted many research efforts. System identification techniques are applied in many fields in order to model and predict the behaviors of unknown and/or very complex systems based on given input-output data [4]. In this way, soft-computing methods [5], which concern computation in an imprecise environment, have gained significant attention.

The main components of soft computing, namely, fuzzy logic, neural network, and evolutionary algorithms have shown great ability in solving complex non-linear system identification and control problems. Many research efforts have been expended to use of evolutionary methods as effective tools for system identification [6]. Among these methodologies, Group Method of Data Handling (GMDH) algorithm is a self-organizing approach by which gradually complicated models are generated based on the evaluation of their performances on a set of multi-input-single-output data pairs (X_i, y_i) $(i=1, 2, ..., M)$. The GMDH was first developed by Ivakhnenko [7] as a multivariate analysis method for complex systems modeling and identification, which 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 [8] whose coefficients are obtained using regression technique. In recent years, however, the use of such self-organizing networks leads to successful application of the GMDH-type algorithm in a broad range of areas in engineering, science, and economics [7].

Moreover, there have been many efforts in recent years to deploy GAs to design artificial neural networks since such evolutionary algorithms are particularly useful for dealing with complex problems having large search spaces with many local optima [9]. In this way, GAs has been used in a feed forward GMDH-type neural network for each neuron searching its optimal set of connection with the preceding layer [10]. In the former reference, authors have proposed a hybrid genetic algorithm for a simplified GMDH-type neural network in which the connection of neurons are restricted to adjacent layers. Moreover a multi-objective genetic algorithm has also been recently used by some of authors to design GMDH-type neural networks considering some conflicting objectives [11].

In this paper head rise and the head loss in a set of forward-curved blades centrifugal fans are numerically investigated using NUMECA. Genetically optimized GMDH type neural networks are then used to obtained polynomial models for the effects of geometrical parameters of the FC fans on both H_R and H_L. Such approach of meta-modeling of those CFD results allows the iterative optimization techniques. The obtained simple polynomial models are then used in a Pareto based multi-objective optimization approach to find the best possible combinations of H_R and H_L, known as the Pareto front. The corresponding variations of design variables, namely, geometrical parameters, known as the Pareto set, constitute some important and informative design principles.

2. CFD simulation of FC blades centrifugal fans

Numerical simulations are performed using Numeca software. Firstly one blade is modeled in Auto blade 3.6 and then the Design 3D environment of Numeca can automatically generate the database with different design variables. The governing equations of incompressible flow are as follows:

- Continuity equation

$$\frac{\partial V_i}{\partial x_i} = 0 \tag{1}$$

- Reynolds averaged momentum equation

$$\frac{DV_i}{Dt} = -\frac{1}{\rho}\frac{\partial p}{\partial x_i} + \nu \frac{\partial^2 V_i}{\partial x_j \partial x_j} - \frac{\partial}{\partial x_j}\overline{u_i u_j} \tag{2}$$

- Standard k–ε model

$$\begin{aligned}\frac{Dk}{Dt} &= \frac{\partial}{\partial x_j}[(C_k \frac{k^2}{\varepsilon} + \nu)\frac{\partial k}{\partial x_i}] - \overline{u_i u_j}\frac{\partial V_i}{\partial x_j} \\ \frac{D\varepsilon}{Dt} &= \frac{\partial}{\partial x_j}[(C_k \frac{k^2}{\varepsilon} + \nu)\frac{\partial \varepsilon}{\partial x_j}] - C_{\varepsilon 1}\frac{\varepsilon}{k}\overline{u_i u_j}\frac{\partial V_i}{\partial x_j} - C_{\varepsilon 2}\frac{\varepsilon^2}{k}\end{aligned} \tag{3}$$

To parameterize the camber line curve, the simple Bezier method is used. Schematically definition of simple Bezier method is shown in figure (1). The design variables in this method are leading edge angle (β_1), trailing edge angle (β_2) and the stagger angle (γ). In this study two sections are defined in the blades, one on hub and one on shroud. It is supposed that β_1, β_2 and γ are equal at hub and shroud section due to the 2D nature of FC blades centrifugal fan, this note can mathematically given by

$$\beta_{1\,Hub} = \beta_{1\,Shroud} = Design\ Variable \tag{4}$$

$$\beta_{2\ Hub} = \beta_{2\ Shroud} = Design\ Variable \quad (5)$$
$$\gamma_{\ Hub} = \gamma_{\ Shroud} = Design\ Variable \quad (6)$$

By changing the geometrical independent parameters, various designs will be generated and evaluated by CFD. Consequently, some meta-models can be optimally constructed using the GMDH-type neural networks, which will be further used for

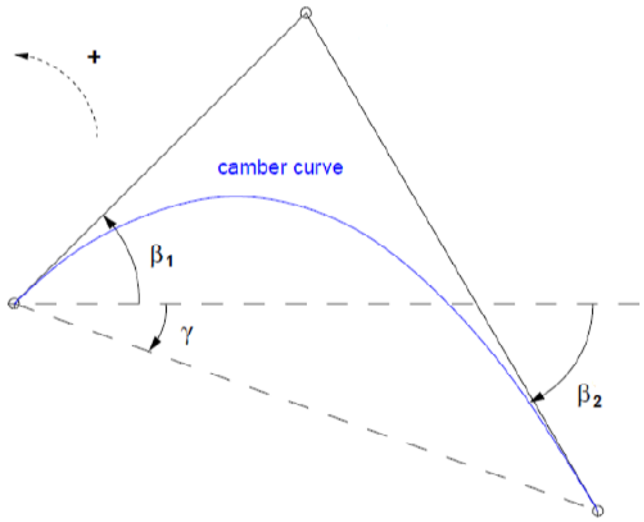

Figure 1: Blade camber line parameterization using simple Bezier method.

multi-objective Pareto based design of such centrifugal fans. In this way, 132 various CFD analyses have been performed due to those different design geometrics.

For CFD grid generation, the Auto Grid environment of Numeca is coupled with the Auto Blade environment. The physical model used in the solver is the Reynolds-Averaged Navier–Stokes equations and the k-ε turbulence model is used. Mass flow, k and ε imposed at the fans inlet, static pressure outlet boundary condition is used at the outlet and finally periodic boundary condition is applied between two blades. The computation is continued until the solution converged with a total residual of less than (-5). A typical pressure contour in one of simulations is shown in figure (2).

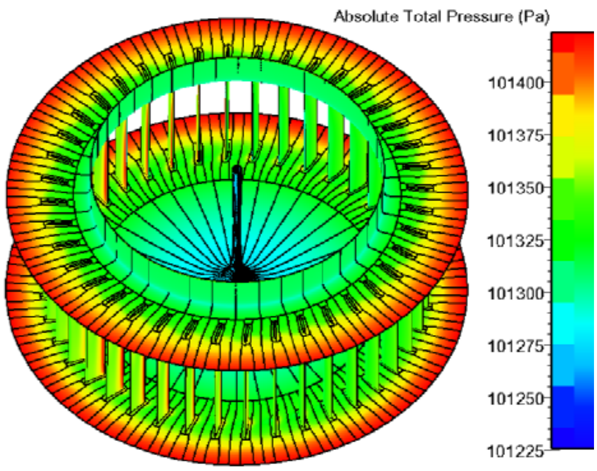

Figure 2: A typical contour of pressure in one of simulations

The results obtained in such CFD analysis can now be used to build the response surface of both the head rise and the head loss for those different 132 geometries using GMDH-type polynomial neural networks. Such meta-models will, in turn, be used for the Pareto-based multi-objective optimization of the FC fans. A post analysis using the CFD software NUMECA is also performed to verify the optimum results using the meta-modeling approach. Finally, the solutions obtained by the approach of this paper exhibit some important trade-offs among those objective functions which can be simply used by a designer to optimally compromise among the obtained solutions.

3. Modeling of H_R and the H_L using GMDH-type neural network

By means of GMDH algorithm a model can be represented as set of neurons in which different pairs of them in each layer are connected through a quadratic polynomial and thus produce new neurons in the next layer. Such representation can be used in modeling to map inputs to outputs. The formal definition of the identification problem is to find a function $\hat{f}$ so that can be approximately used instead of actual one, f in order to predict output $\hat{y}$ for a given input vector $X = (x_1, x_2, x_3, ..., x_n)$ as close as possible to its actual output y. Therefore, given M observation of multi-input-single-output data pairs so that

$$y_i = f(x_{i1}, x_{i2}, x_{i3}, ..., x_{in}) \quad (i=1, 2 ... M), \tag{7}$$

It is now possible to train a GMDH-type neural network to predict the output values $\hat{y}_i$ for any given input vector

$X = (x_{i1}, x_{i2}, x_{i3}, ..., x_{in})$, that is

$$\hat{y}_i = \hat{f}(x_{i1}, x_{i2}, x_{i3}, ..., x_{in}) \quad (i=1, 2 ... M), \tag{8}$$

The problem is now to determine a GMDH-type neural network so that the square of difference between the actual output and the predicted one is minimized, that is

$$\sum_{i=1}^{M} [\hat{f}(x_{i1}, x_{i2}, x_{i3}, ..., x_{in}) - y_i]^2 \rightarrow \min \tag{9}$$

General connection between inputs and output variables can be expressed by a complicated discrete form of the Volterra functional series in the form of

$$y = a_0 + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij} x_i x_j + \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n} a_{ijk} x_i x_j x_k + ... \tag{10}$$

where is known as the Kolmogorov-Gabor polynomial [8]. This full form of mathematical description can be represented by a system of partial quadratic polynomials consisting of only two variables (neurons) in the form of

$$\hat{y} = G(x_i, x_j) = a_0 + a_1 x_i + a_2 x_j + a_3 x_i x_j + a_4 x_i^2 + a_5 x_j^2 \tag{11}$$

There are two main concepts involved within GMDH-type neural networks design, namely, the parametric and the structural identification problems. In this way, some authors presented a hybrid GA and singular value decomposition (SVD) method to optimally design such polynomial neural networks [10]. The methodology in these references has been successfully used in this paper to obtain the polynomial models of H_R and H_L. The obtained GMDH-type polynomial models have shown very good prediction ability of unforeseen data pairs during the training process which will be presented in the following sections.

The input–output data pairs used in such modeling involve two different data tables obtained from CFD simulation discussed in Section 2. Both of the tables consist of four variables as inputs, namely, the geometrical parameters of the FC fans γ, β_1, β_2 (figure (1)) and N (number of blades) and outputs, which are H_R and H_L. The tables consist of a total of 132 patterns, which have been obtained from the numerical solutions to train and test such

GMDH type neural networks. However, in order to demonstrate the prediction ability of the evolved GMDH type neural networks, the data in both input–output data tables have been divided into two different sets, namely, training and testing sets. The training set, which consists of 112 out of the 132 input–output data pairs for H_R and H_L, is used for training the neural network models. The testing set, which consists of 20 unforeseen input–output data samples for H_R and H_L during the training process, is merely used for testing to show the prediction ability of such evolved GMDH type neural network models. The GMDH type neural networks are now used for such input–output data to find the polynomial models of head rise and head loss with respect to their effective input parameters. In order to design genetically such GMDH type neural networks described in the previous section, a population of 10 individuals with a crossover probability (*Pc*) of 0.7 and mutation probability (*Pm*) 0.07 has been used in 500 generations for H_R and H_L. The corresponding polynomial representation for Head Rise (H_R) is as follows:

$$Y_1 = -27.356 + 0.338\ \beta_2 + 1.677\ N - 0.00345\ \beta_2^{\ 2} - 0.0234\ N^2 + 0.00291\ N\ \beta_2 \tag{12a}$$

$$Y_2 = -20.196886 - 0.00586\beta_1 + 1.7555\ N + 0.00054\beta_1^{\ 2} - 0.0234N^2 + 0.00198\beta_1 N \tag{12b}$$

$$Y_3 = -19.7199 - 0.10393\gamma + 1.73866N + 0.00507\gamma^2 - 0.02340N^2 + 0.0039480\gamma N \tag{12c}$$

$$Y_4 = -1.552 + 0.18001\ \beta_1 + 0.4275\ \beta_2 - 0.001652\beta_1^{\ 2} - 0.003306\ \beta_2^{\ 2} - 0.00013\beta_1\ \beta_2 \tag{12d}$$

$$Y_5 = 8.78175 + 0.502008Y_2 - 1.1355\mathrm{Y}_1 - 0.04922Y_2^{\ 2} + +0.000709\mathrm{Y}_1^{\ 2} + 0.1217Y_2\mathrm{Y}_1 \tag{12e}$$

$$Y_6 = -6.2660 + 1.05304Y_4 - 0.044003\mathrm{Y}_3 - 0.016115Y_4^{\ 2} + 0.026433\mathrm{Y}_3^{\ 2} + 0.02430Y_4\mathrm{Y}_3 \tag{12f}$$

$$H_R = 1.898441 - 0.45095Y_5 + 1.18816\mathrm{Y}_6 - 0.14790\ Y_5^{\ 2} - 0.17717\mathrm{Y}_6^{\ 2} + 0.3359Y_5\mathrm{Y}_6 \tag{12g}$$

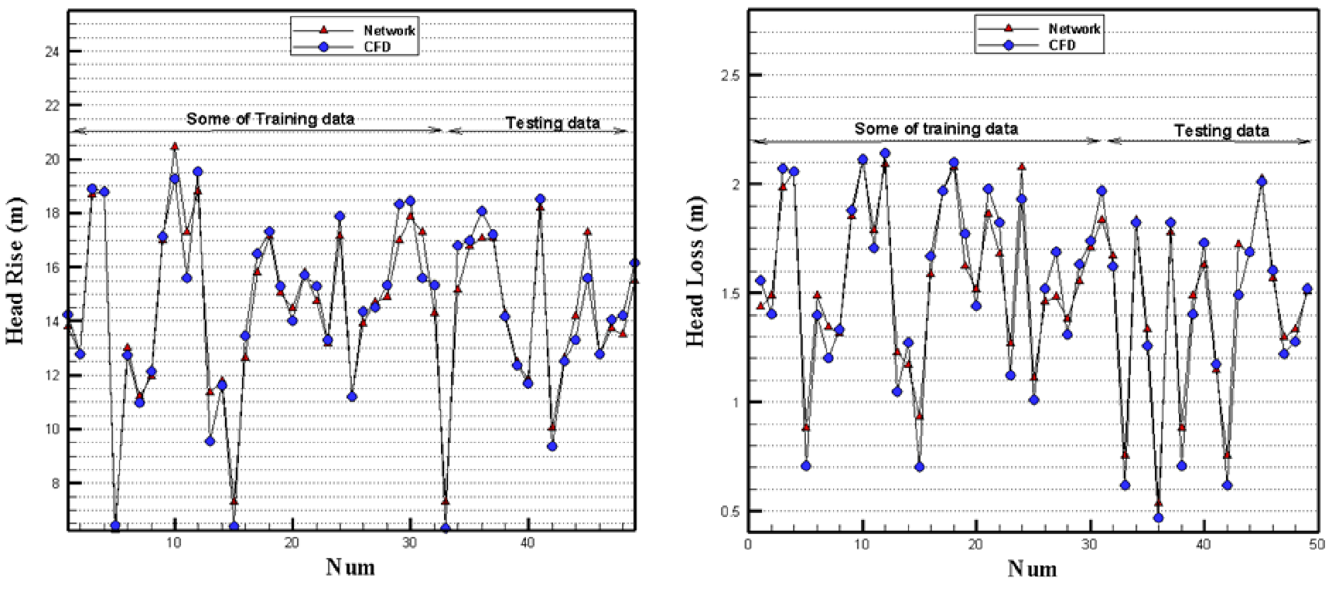

Figure3: CFD vs. Network

Similarly, the corresponding polynomial representation of the model for Head Loss (H_L) is in the form of

$$Y_1' = 1.2905 - 0.0799\gamma + 0.01905\beta_1 + 0.00382\gamma^2 + 3.383\mathrm{e}-005\beta_1^{\ 2} - 0.000769\gamma\,\beta_1 \tag{13a}$$

$$Y_2' = -2.8676 + 0.02454\beta_2 + 0.1849\ N - 0.00025\beta_2^{\ 2} - 0.002538N^2 + 0.000339N\,\beta_2 \tag{13b}$$

$$H_L = -2.93563 + 4.11599Y_1' + 0.4002\mathrm{Y}_2' - 1.4661Y_1'^{\,2} - 0.10065\mathrm{Y}_2'^{\,2} + 0.602920Y_1'\mathrm{Y}_2' \tag{13c}$$

The very good behavior of such GMDH type neural network model for head rise and head loss is also depicted in figure (3), both for the training and testing data. It is evident that the evolved GMDH type neural network in terms of simple polynomial equations successfully model and predict the outputs of the testing data that have not been used during the training process. The models obtained in this section can now be utilized in a Pareto multi-objective optimization of the FC centrifugal fans considering both H_R and H_L 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.

4. Multi-objective optimization of FC centrifugal fans

In order to investigate the optimal performance of the FC centrifugal fan in different conditions, the polynomial neural network models obtained in section 3 are now employed in a multi-objective optimization procedure. The two conflicting objectives in this study are Head Rise (H_R) and Head Loss (H_L) that is to be simultaneously optimized with respect to the design variables γ, β_1, β_2 (figure (1)) and N (Number of blades). The multi-objective optimization problem can be formulated in the following form:

$$\begin{cases} \textit{Maximize} \quad \textit{Head Rise } (H_R) = f_1\,(\gamma, \beta_1, \beta_2, N) \\ \textit{Minimize} \quad \textit{Head Loss } (H_L) = f_2\,(\gamma, \beta_1, \beta_2, N) \\ \qquad\qquad 7^o \le \gamma \le 25^{\,o} \\ \textit{Subject to} \qquad 12^o \le \beta_1 \le 47^{\,o} \\ \qquad\qquad 25^{\,o} \le \beta_2 \le 60^{\,o} \\ \qquad\qquad 25 \le N \le 40 \end{cases} \tag{14}$$

The evolutionary process of Pareto multi-objective optimization is accomplished by using the recently developed algorithm, namely, the ϵ-elimination diversity algorithm by some of authors [10, 11] where a population size of 60 has been chosen in all runs with crossover probability P_c and mutation probability P_m as 0.7 and 0.07 respectively.

Figure (4) depicts the obtained non-dominated optimum design points as a Pareto front of those two objective functions. It is clear from this figure that all the optimum design points in the Pareto front are non-dominated and could be chosen by a designer as optimum FC fan. Evidently, choosing a better value for any objective function in the Pareto front would cause a worse value for another objective. The corresponding decision variables of the Pareto front shown in figure (4) are the best possible design points so that if any other set of decision variables is chosen, the corresponding values of the pair of objectives will locate a point inferior to this Pareto front. Such inferior area in the space of the two objectives is in fact bottom/right side of figure (4).

In figure (4), the design points A and D stand for the best head loss and the best head rise. It is now desired to find a trade-off optimum design points compromising both objective functions. This can be achieved by the method employed in this paper, namely, the mapping method. In this method, the values of objective functions of all non-dominated points are mapped into interval 0 and 1.Using the sum of these values for each non-dominated point, the

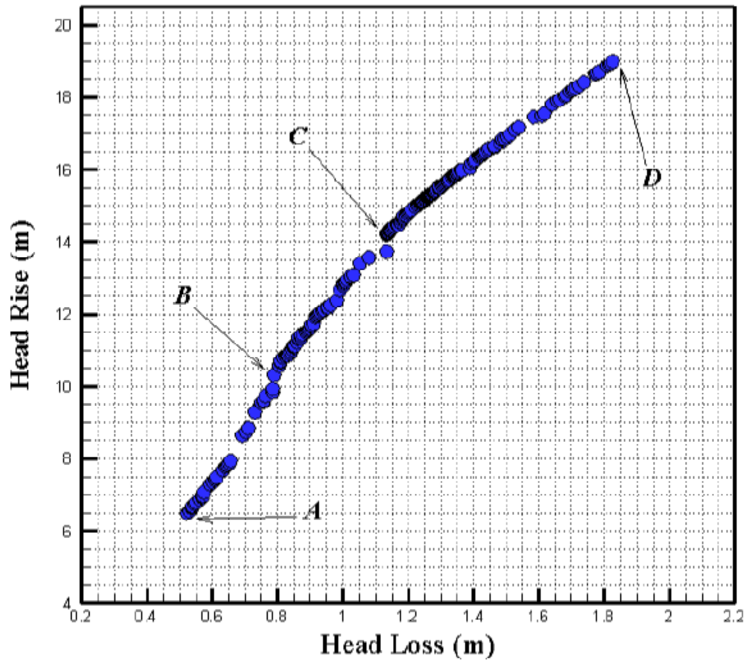

Figure 4: Pareto front of head rise and head loss

trade-off point simply is one having the minimum sum of those values. Consequently, optimum design point *C* is the trade-off points which have been obtained from the mapping method.

Moreover, the other optimum design point, *B* can be simply recognized from figure (4), which exhibit important optimal design concepts. In fact, optimum design point *B* obtained in this paper exhibits an increase in head loss (about 23.58%) in comparison with that of point *A* whilst its head rise improves about 30.6% in comparison with that of *A* The corresponding design variables and objective functions of optimum design points, *A, B, C* and *D* are shown in table (1). These points clearly demonstrate tradeoffs in objective functions head rise and head loss from which an appropriate design can be compromisingly chosen.

Table 1: The values of objective functions and their associated design

variables of the optimum points

Point	γ (deg)	β_1(deg)	β_2(deg)	N	H_R (m)	H_L (m)
A	13.48	12.36	25.24	25	6.503	0.520
B	12.54	12.14	57.82	25	10.695	0.809
C	13.33	12.01	57.57	33	14.376	1.156
D	17.38	42.19	58.57	38	18.981	1.827

The Pareto front obtained from the GMDH-type neural network model (figure (4)) has been superimposed with the corresponding CFD simulation results in figure (5). It can be clearly seen from this figure that such obtained Pareto front lies on the best possible combination of the objective values of CFD data, which demonstrate the effectiveness of this paper, both in deriving the model and in obtaining the Pareto front.

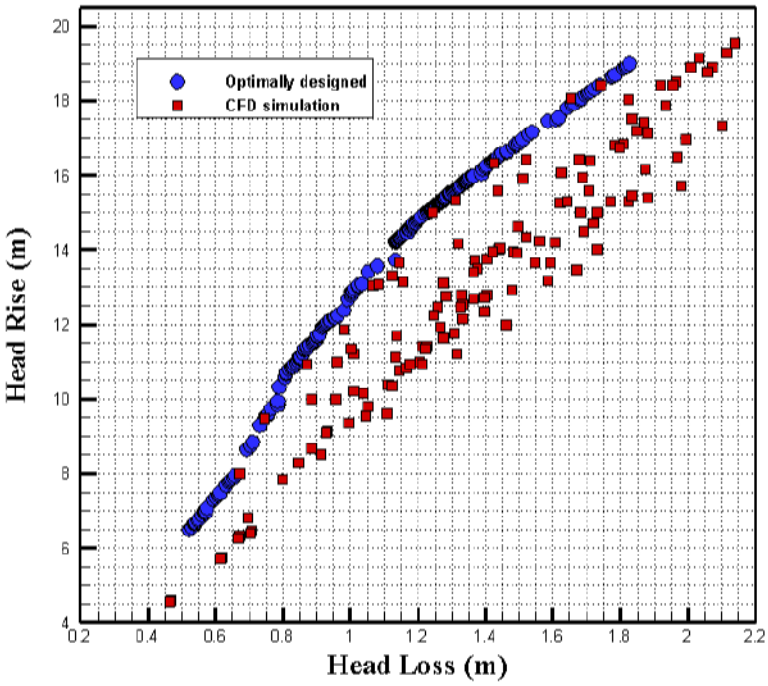

Figure 5: Overlay graph of the obtained optimal Pareto front with the numerical data.

5. Conclusion

Genetic algorithms have been successfully used both for optimal design of generalized GMDH type neural networks models of Head Rise and Head Loss in FC centrifugal fans and for multi-objective Pareto based optimization of such processes. Two different polynomial relations for H_R and H_L have been found by evolved GS-GMDH type neural networks using some CFD simulations for input–output data of the fans. The derived polynomial models have been then used in an evolutionary multi-objective Pareto based optimization process so that some interesting and informative optimum design aspects have been revealed for fans with respect to the design variables such as geometrical parameters of γ, β_1, β_2 (figure (1)) and number of blades (N). Consequently, some very important tradeoffs in the optimum design of FC centrifugal fans have been obtained and proposed based on the Pareto front of two conflicting objective functions. Such combined application of GMDH type neural network modeling of input–output data and subsequent non-dominated Pareto optimization process of the obtained models is very promising in discovering useful and interesting design relationships.

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