Numerical Study and GMDH type Neural Networks Modelling of Heat Transfer and Flow Characteristics in Microchannels

M. Borji, K. Salmalian, M. Soleimani, R. Najar

Abstract— Three-dimensional heat transfer characteristics and pressure drop of water flow in a set of rectangular microchannels are numerically investigated using Fluent and compared with those of experimental results. The full Navier-Stoke's approach is employed for this kind of narrow channels for the water flow assessments. The complete form of the energy equation accompanying the dissipation terms is also linked to the momentum equations. The calculated Nusselt numbers in different conditions show a good agreement with experimental results. Afterwards, two metamodels based on the evolved group method of data handling (GMDH) type neural networks are then obtained for modelling of both pressure drop (DP) and Nusselt number (Nu) with respect to design variables such as geometrical parameters of microchannels, the amount of heat flux and the Reynolds number. It is depicted that the evolved GMDH type neural network in terms of simple polynomial equations successfully model and predict the outputs of the testing data.

Keywords— Microchannel, Pressure Drop, GMDH type Neural Network.

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I. Introduction

The increasing incorporation of electronic systems requires innovative, small scale and highly effective cooling techniques for the removal of a large amount of heat from a small area in order to avoid its temperature from rising significantly and operate electronic devise at an optimum temperature. Many techniques have been developed for controlling and removing the heat generated in such a case. Among them, the microchannel heat sink is of special interest. Microchannel heat sink is a structure with many micro scale channels of large aspect ratio built on the back of the microchip, and a liquid is forced through these passages to carry out the energy. The microchannel heat sink at first proposed by Tuckermann and Pease [1], they demonstrated that the microchannel heat sinks, consisting of micro rectangular flow passages, have a higher heat transfer coefficient in laminar flow regime than that in turbulent flow through conventionally-sized devices. Since pioneering work of Tuckerman and Pease [1], many experimental, analytical and numerical investigations are reported [2, 3, 4, 5, 6, 7, 8, 9, 10, 11, and 12]. Peng and Wang [2] and Peng and Peterson [3] systematically examined the forced flow and heat transfer characteristics of water and binary mixtures flowing through rectangular microchannels. It was observed that laminar flow transition occurred at Reynolds number between 200 and 700. Those results showed that the flow velocity and heat transfer rate in the microchannels largely depend on both their geometry and the coolant type and properties [4]. Therefore, they may differ from those that are typical for macrochannels. The flow of water and various biological fluids in straight silicon microchannels with glass walls was studied by Wilding et al. [5]. It was shown that there is an about 50% increase in the Darcy friction coefficient as compared to the theoretical prediction. Similar results were obtained by Jiang et al. [6], who studied the flow of water through microchannels with rectangular and trapezoidal cross sections. The flow and heat transfer characteristics in microchannels could not be adequately predicted by the theories and correlations developed for macroscale channels. However, experimental results illustrate that continuity assumptions can be used, although there are different insights about the Navier–Stokes equations. Philips [7] indicated that thermal resistance smaller than 0.1 °C/(W/cm2) can be achieved in microscale channels. Federov and Viskanta [8] reported that the thermal resistance decreases with Reynolds number and reaches an asymptote at high Reynolds numbers. Accurate prediction of heat transfer coefficients also requires that thermal boundary conditions be correctly simulated [8, 9]. The design and optimization of such microchannel passages in a direct heat sink is important from an operational standpoint. Pressure drop considerations will determine the required pumping power. The microchannels are optimized using the flow channel dimensions as design variables in a range that can be fabricated. Knight et al. [13, 14] presented an optimization scheme that included both laminar and turbulent flow. Another excellent report in the field of microchannel optimization can be seen in [15]

However, optimization of such microchannels is, indeed, a multi-objective optimization problem rather than a single objective optimization problem that has been considered so far in the literature. Both the pressure drop and the Nusselt number of the flow and heat transfer in microchannels are important objective functions to be optimized simultaneously in such a real world complex multi-objective optimization problem. These objective functions are either obtained from

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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 metamodel is constructed over the response surface from the numerical or experimental data. 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 [16]. In this way, soft computing methods [17], 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 evolutionary methods as effective tools for system identification [18–23]. 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 performances on a set of multi-input, single output data pairs (Xi,yi) (i = 1,2,. . . ,M). The GMDH was first developed by Ivakhnenko [24] as a multivariate analysis method for complex systems modelling and identification. In this way, the GMDH was used to circumvent the difficulty of having a priori knowledge of the mathematical model of the process being considered. Therefore, the GMDH can be used to model complex systems without having specific knowledge of the systems. The main idea of the GMDH is to build an analytical function in a feed forward network based on a quadratic node transfer function [25] whose coefficients are obtained using the regression technique.

In this paper, the compatibility and effectiveness of the Navier–Stokes and energy correlations in microscale channels is numerically verified using finite volume based on the experimental results of Tuckermann and Pease [1]. Next, genetically optimized GMDH type neural networks are used to obtained polynomial models for the effects of geometrical parameters of the microchannel, the amount of heat flux and the Reynolds number on both pressure drop and Nusselt number.

II. Modelling using GMDH type neural networks

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

$$y_i = f(x_{i1}, x_{i2}, x_{i3}, ..., x_{in}) \quad, (i = 1,2,3,\ldots, M) \tag{1}$$

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

$$\hat{y}_i = \hat{f}(x_{i1}, x_{i2}, x_{i3}, ..., x_{in}) \quad, (i = 1,2,3,\ldots, M) \tag{2}$$

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

$$\sum_{i=1}^{M} [\hat{f}(x_{i1}, x_{i2}, x_{i3}, ..., x_{in}) - y_i]^2 \to \min \tag{3}$$

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

$$y = a_0 + \sum_{i=1}^{n} a_i x_i + \sum_{i=1}^{n}\sum_{j=1}^{n} a_{ij} x_i x_j + \sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n} a_{ijk} x_i x_j x_k + ... \tag{4}$$

Where is known as the Kolmogorov-Gabor polynomial [22-24]. 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

$$\hat{y} = G(x_i, x_j) = a_0 + a_1 x_i + a_2 x_j + a_3 x_i x_j + a_4 x_i^2 + a_5 x_j^2 \tag{5}$$

In this way, such partial quadratic description is recursively used in a network of connected neurons to build the general mathematical relation of inputs and output variables given in equation (4). The coefficients a_i in equation (5) are calculated using regression techniques [22, 24] so that the difference between actual output, y, and the calculated one, $\hat{y}$ for each pair of x_i, x_j as input variables is minimized. Indeed, it can be seen that a tree of polynomials is constructed using the quadratic form given in equation (5) whose coefficients are obtained in a least-squares sense. In this way, the coefficients of each quadratic function G_i are obtained to optimally fit the output in the whole set of input-output data pair, that is

$$E = \frac{\sum_{i=1}^{M} (y_i - G_i)^2}{M} \to \min \tag{6}$$

In the basic form of the GMDH algorithm, all the possibilities of two independent variables out of total n input variables are taken in order to construct the regression polynomial in the form of equation (5) that best fits the dependent observations (y_i , *i=1, 2, …, M*) in a least-squares sense. Consequently, $\binom{n}{2}=\frac{n(n-1)}{2}$ neurons will be built up in the first hidden layer of the feed forward network from the observations $\{(y_i, x_{ip}, x_{iq});\ (i=1, 2,\ldots, M)\}$ for different $p,q \in \{1,2,\ldots,n\}$. In other words, it is now possible to construct M data triples $\{(y_i, x_{ip}, x_{iq});\ (i=1, 2\ldots M)\}$ from observation using such $p,q \in \{1,2,\ldots,n\}$ in the form

$$\left[\begin{array}{cc:c} x_{1p} & x_{1q} & y_1 \\ x_{2p} & x_{2q} & y_2 \\ \hdashline x_{Mp} & x_{Mq} & y_M \end{array}\right]$$

Using the quadratic sub-expression in the form of equation (5) for each row of M data triples, the following matrix equation can be readily obtained as

$$A\mathbf{a} = Y \tag{7}$$

Where $\mathbf{a}$ is the vector of unknown coefficients of the quadratic polynomial in equation (5)

$$\mathbf{a} = \{a_0, a_1, a_2, a_3, a_4, a_5\} \tag{8}$$

And

$$Y = \{y_1, y_2, y_3, \ldots, y_M\}^T \tag{9}$$

Is the vector of output's value from observation. It can be readily seen that

$$A = \left[\begin{array}{cccccc} 1 & x_{1p} & x_{1q} & x_{1p}x_{1q} & x_{1p}^2 & x_{1q}^2 \\ 1 & x_{2p} & x_{2q} & x_{2p}x_{2q} & x_{2p}^2 & x_{2q}^2 \\ \hdashline 1 & x_{Mp} & x_{Mq} & x_{Mp}x_{Mq} & x_{Mp}^2 & x_{Mq}^2 \end{array}\right] \tag{10}$$

The least-squares technique from multiple-regression analysis leads to the solution of the normal equations in the form of

$$\mathbf{a} = (A^T A)^{-1} A^T Y \tag{11}$$

Which determines the vector of the best coefficients of the quadratic Eq. (5) for the whole set of M data triples. It should be noted that this procedure is repeated for each neuron of the next hidden layer according to the connectivity topology of the network. However, such a solution directly from normal equations is rather susceptible to round off errors and, more importantly, to the singularity of these equations.

Singular value decomposition (SVD) is the method for solving most linear least square problems in which some singularities may exist in the normal equations. The SVD of a matrix, $A \in R^{M\times 6}$ is a factorization of the matrix into the product of three matrices, a column orthogonal matrix $U \in R^{M\times 6}$, a diagonal matrix $W \in R^{6\times 6}$ with non-negative elements (singular values) and an orthogonal matrix $V \in R^{6\times 6}$ such that;

$$A \tag{12}$$

The problem of optimal selection of the vector of the coefficients in equations (8) and (11) is firstly reduced to finding the modified inversion of the diagonal matrix W (in which the reciprocals of zero or near zero singulars (according to a threshold) are set to zero). Then, such optimal a is calculated using the following relation;

$$a \tag{13}$$

Such parametric identification problem is part of the general problem of modelling when structure identification is considered together with the parametric identification problem simultaneously. In this work, a new encoding scheme is presented in an evolutionary approach for simultaneous determination of structure and parametric identification of GMDH type neural networks [26].

Stochastic methods are commonly used in the training of neural networks in terms of associated weights or coefficients that have successfully performed better than traditional gradient based techniques [26 and references therein]. The literature shows a wide range of evolutionary design approaches either for architectures or for connection weights separately in addition to efforts for them simultaneously. In most GMDH type neural networks, the neurons in each layer are only connected to neurons in its adjacent layer as was the case in Methods I and II previously reported in Ref. [25]. Taking this advantage, it was possible to present a simple encoding scheme for the genotype of each individual in the population as already proposed by the authors [25]. The encoding schemes in generalized GMDH type neural networks (GSGMDH) must demonstrate the ability of representing different lengths and sizes of such neural networks.

In a GS-GMDH type neural network, Figure 1, neuron *ad* in the first hidden layer is connected to the output layer by directly going through the second hidden layer. Therefore, it is now very easy to notice that the name of the output neuron (network's output) includes *ad* twice as *abbcadad*. In other words, a virtual neuron named *adad* has been constructed in the second hidden layer and used with *abbc* in the same layer to make the output neuron *abbcadad* as shown in Figure 1. It should be noted that such repetition occurs whenever a neuron passes some adjacent hidden layers and connects to another neuron in the next 2nd, or 3rd, or 4th, or . . . following hidden layer. In this encoding scheme, the number of repetitions of that neuron depends on the number of passed hidden layers, $\tilde{n}$, and is calculated as $2^{\tilde{n}}$. It is easy to realize that a chromosome such as *abab bcbc*, unlike chromosome *abab acbc* for example, is not a valid one in GS-GMDH type networks and has to be simply re-written as *abbc* [26, 27].

The genetic operators of crossover and mutation can now be implemented to produce two offspring from two parents. The natural roulette wheel selection method is used for choosing two parents for producing two offspring.

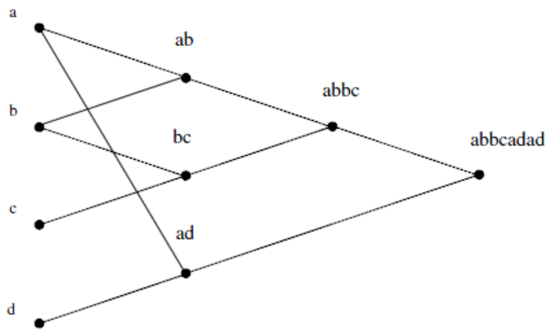

Fig. 1 A generalized GMDH network structure of a chromosome.

The crossover operator for the two selected individuals is simply accomplished by exchanging the tails of two chromosomes from a randomly chosen point as shown in Figure 2.

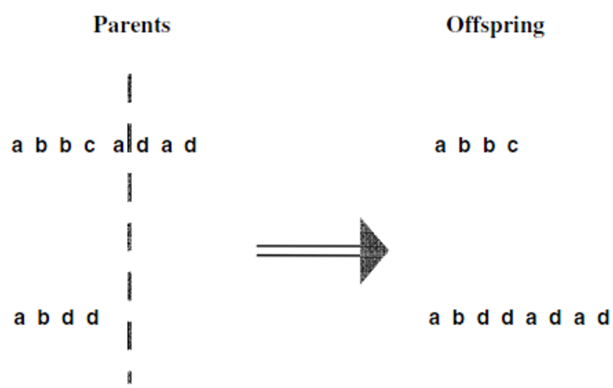

Fig. 2 Crossover operation for two individuals in generalized GMDH type networks.

It should be noted; that such a point could only be chosen randomly from the set $\{2^1, 2^2, \ldots, 2^{n+1}\}$ where n_1 is the number of hidden layers of the chromosome with the smaller length. It is very evident from Figures 2 and 3 that the crossover operation can certainly exchange the building blocks information of such generalized GMDH type neural networks so that the two types of generalized GMDH type and conventional GMDH type neural networks can be converted to each other, as can be seen from Figure 3.

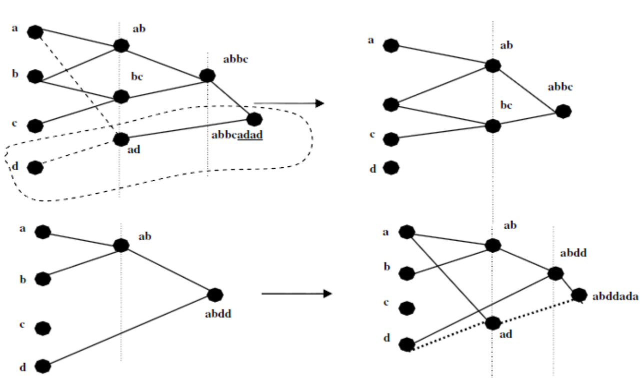

Fig. 3 Crossover operation on two generalized GMDH type networks.

In addition, such crossover operation can also produce different lengths of chromosomes that, in turn, lead to different sizes of either the generalized GMDH type or conventional GMDH type network structures. Similarly, the mutation operation can contribute effectively to the diversity of the population. This operation is simply accomplished by changing one or more symbolic digits as genes in a chromosome to other possible symbols, for example, <u>*abbcadad*</u> to <u>*abbccdad*</u>. It is very evident that the mutation operation can also convert a generalized GMDH type network to a conventional GMDH type network or vice versa. It should be noted that such evolutionary operations are acceptable provided a valid chromosome is produced. Otherwise, these operations are simply repeated until a valid chromosome is constructed.

The incorporation of the genetic algorithm into the design of such GMDH type neural networks starts by representing each network as a string of concatenated substrings of alphabetical digits. The fitness, ($\emptyset$), of each entire string of symbolic digits, which represents a GMDH type neural network to model the explosive cutting process is evaluated in the form;

$$\emptyset \qquad (14)$$

where E, the mean square of error given by equation (6), is minimized through the evolutionary process by maximizing the fitness $\emptyset$. The evolutionary process starts by randomly generating an initial population of symbolic strings, each as a candidate solution. Then, using the aforementioned genetic operations of roulette wheel selection (crossover and mutation), the entire populations of symbolic strings is improve gradually. In this way, GMDH type neural network models with progressively increasing fitness, $\emptyset$, are produced until no further significant improvement is achievable [26-27].

III. Physical Model and Computational Domain

A schematic view, physical, and computational domain of such microchannels is depicted in Figure 4, Figure 5, and Figure 6, respectively.

Heat is removed primarily by conduction through the solid and then dissipated away by convection of the cooling fluid in the microchannel. The microchannel has been studied is made of silicon with thermal conductivity (k) of 148 W/m.K. At the bottom, a uniform heat flux of q'' arises from an electric chip that is connected to the microchannel. At the top of the channels, there is a Pyrex plate which makes an adiabatic condition. The width of microchannels and the wall thickness are represented by Wc and Ws, respectively.

The thickness of the silicon substrate through which the heat flux is transformed to the cooling fluid flowing in channels can be simply recognized as Ht-Hc, according to Figure 4. The total length and width of microchannels are Lh and Wt whose values of five different cases are in Table 1. Moreover, steady incompressible and laminar fluid flow and steady heat transfer, with negligible radiative heat transfer and constant solid and fluid property have been assumed in computations.

The inlet temperature of cooling water through the channels is 20ºC. A microchannel in the center parts of the plate will be considered in current work. As a result of the symmetry of the rectangular channel, we will center the computational domain in a half channel as shown in Figure 6.

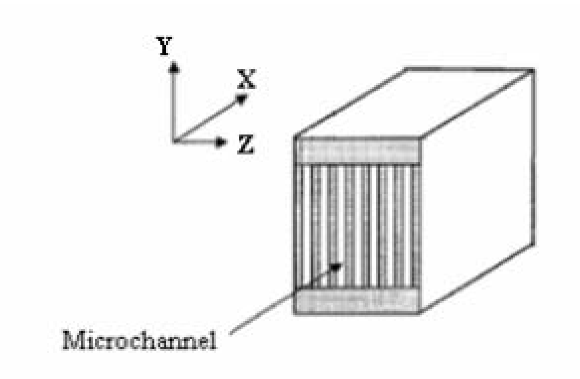

Fig. 4 Schematic view of Microchannel.

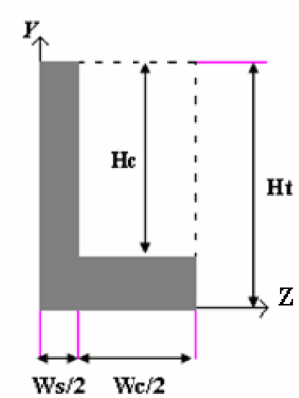

Fig. 5 Physical Model.

TABLE 1
FORE DIFFERENT CASES OF MICROCHANNEL

Description	Case 0	Case 1	Case 2	Case 3	Case4
$L_t(cm)$	2	2	1.4	1.4	1.4
$W_t(cm)$	1.5	1.5	2	2	2
$W_c(\mu m)$	64	64	56	55	50
$W_S(\mu m)$	36	36	44	45	50
$H_t(\mu m)$	489	489	533	430	458
$H_c(\mu m)$	280	280	320	287	302
Number of Channels	150	150	200	200	200

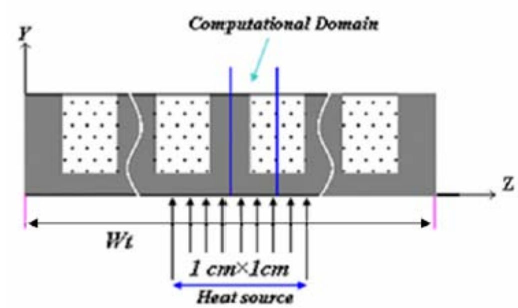

Fig. 6 Computational Domain.

IV. GOVERNING EQUATION

Assuming a laminar fully developed flow in rectangular channels in positive x-direction, the components of velocity satisfy $u = u(y, z)$ and $v = w = 0$ in terms of Cartesian coordinate system. The equation of motion is written as follows:

$$\frac{\partial}{\partial} \tag{15}$$

As presented in Figure 4, a silicon wafer plate with a large number of microchannels is connected to the chip. A liquid is forced to flow through these channels to remove the heat. All microchannels are assumed to have a uniform rectangular cross-section with geometric parameters as shown in Table 1. For a steady-state, fully developed, laminar flow in a microchannel, the energy equation (with considering of the axial thermal conduction in flow direction and the viscous dissipation) for the cooling liquid takes the specific form:

(16)

Where T, $\propto_f$, and C_{pf} are the temperature, thermal diffusivity and specified heat capacity of the cooling liquid, respectively. Based on presented computational domain, the adiabatic condition can be used along the channel symmetric center line:

(17)

At the bottom of channels, a uniform heat flux of q" is imposed over the heat sink, and can be expressed as:

(18)

Hear k_f is the thermal conductivity of the liquid coolant. Since the thermal conductivity of the glass is about two-order of magnitude lower than that the top boundary is insulated.

This is a conservative assumption which will lead to slight underestimation of the overall heat transfer coefficient. This assumption yields:

(19)

V. CFD SIMULATION AND COMPARISION WITH EXPERIMENTAL RESULTS

In current work finite volume method of Patankar [32] is used to solve the continuity, momentum, and energy equations numerically. Since a detailed discussion of the FVM is available in Patankar [32], only a very brief description of the main features of this method is given here. In the FVM, the domain is divided into a number of control volumes such that there is one control volume surrounding each grid point. The grid point is located in the center of a control volume. The governing equation is integrated over each control volume to derive an algebraic equation containing the grid point values of the dependent variable. The discretization equation then expresses the conservation principle for a finite control volume just as the partial differential equation expresses it for an infinitesimal control volume. The resulting solution implied that the integral conservation of quantities such as mass, momentum, and energy is exactly satisfied for any control volume and of course, for the whole domain. The power-low scheme is used to model the combined convection diffusion effects in the transport equations. The SIMPLER algebraic of Patankar is used to resolve the pressure-velocity coupling. The resulting algebraic equations are solved using a line-by-line Tri-Diagonal matrix Algorithm.

On the other hand, the results of the Tuckermann and Pease experiments [1] in terms of the amount of heat flux and thermal resistance, which can be simply computed using;

(20)

are given in Table 2. In equation (20) T_{max} and T_{in} respects the maximum measured outlet and the inlet temperature of the cooling water, respectively, and q is the heat flux. It is shown that sufficiently reasonable agreement exists in such comparison, and therefore, the full Navier–Stokes approach can be deployed for such microchannels flow and heat transfer computation with a hydraulic diameter of about 100 μm. In this way, the effects of geometrical parameters such as H_t/D_h and H_c/D_h, the Reynolds number (Re) and heat flux (q) on both pressure drop (DP) and Nusselt number (Nu) can be numerically investigated. The Reynolds number (Re) and Nusselt number (Nu) are computed as:

(21)

and

(22)

where the hydraulic diameter D_h is $D_h = \frac{H_t W_c}{H_t + W_c}$, ρ is the density of cooling water, μ is the viscosity of the cooling water and V_{ave} is the average water flow velocity. The heat fluxes used in the computations are the same as given in Table 2 involving four different values of 34.6, 181, 277, and 790 W/cm^2 for six different water flow velocities of 0.5, 1, 2, 3, 4 and 5 m/s to ensure the regime of flow in the different channels. Thus, 24 different cases can be obtained for pressure drop (DP) and 96 cases for Nusselt number (Nu). It should be noted that Nu is computed in nine different locations through the length of the channel and an average value is considered for Nu of a particular case. Thus, 96 runs are needed to establish the input–output data table for Nusselt number for the four different geometric cases, four different values of heat flux and six different values of flow velocity. Consequently, such input–output data table, obtained from experimentally validated Navier– Stokes computations (24 for DP and 96 for Nu), can now be used for a meta-modelling approach (e.g. a GMDH type neural network model).

TABLE 2
THERMAL RESISTANCE COMPARISION

Case	$q(\frac{W}{cm^2})$	$R(cm^2K/W)$		Error (%)
		Experimental	Numerical	
0	34.6	0.277	0.253	8.5
1	34.6	0.280	0.246	12.1
2	181	0.110	0.116	5
3	277	0.113	0.101	8.10
4	790	0.090	0.086	3.94

VI. MODELLING OF NU AND ΔP USING GMDH TYPE NEURAL NETWORK

The input-output data pairs used in such modeling involve two different data tables obtained from CFD simulation discussed in section V. The first table consists of four variables as inputs, namely, dimensionless geometrical parameter of microchannel (H_t/D_h, H_c/D_h), Reynolds number (Re), and heat flux (q), and one output which is Nu. The second table consists of three variables as input, namely, H_t/D_h, H_c/D_h and Re as inputs and another output which is ΔP. The first table consists of a total 96 pattern numbers and second table consist of 24 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 80 out of 96 input-output data pairs for Nu and 20 out of 24 input-output data pairs for ΔP, is used for training the neural network models using the method presented in section II. The testing set, which consist of 16 unforeseen input-output data samples for Nu and four for ΔP, 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 Nu and ΔP with respect to their effective input parameters. In order to design genetically such GMDH type neural networks described in section 2, a population of 25 individuals with a crossover probability (Pc) of 0.7 and mutation probability (Pm) 0.08 has been used in 200 generations for Nu and a population of 20 individuals with a Pc=0.7 and Pm=0.08 has been used in 250 generations for ΔP. The structures of the evolved two hidden layer GMDH type neural network for Nu and ΔP are shown in Figures 5, and 6 corresponding to the genomes representation of (abbcbccd) and (acbbaabc) for Nu and ΔP respectively. For the Nu representation, a, b, c and d stand for H_t/D_h, H_c/D_h, q and Re respectively. For the ΔP representation, a, b and c stand for H_t/D_h, H_c/D_h, Re respectively.

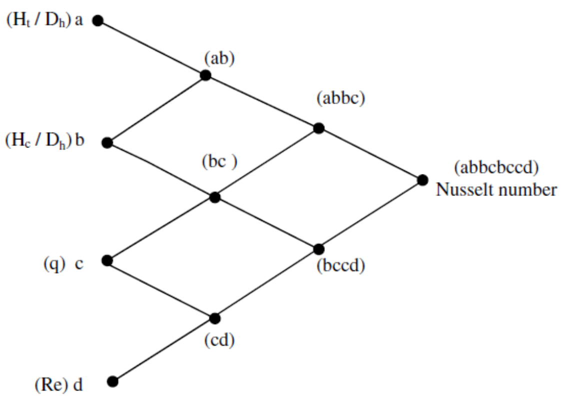

Fig. 5 Evolved structure of generalized GMDH type network for Nusselt number.

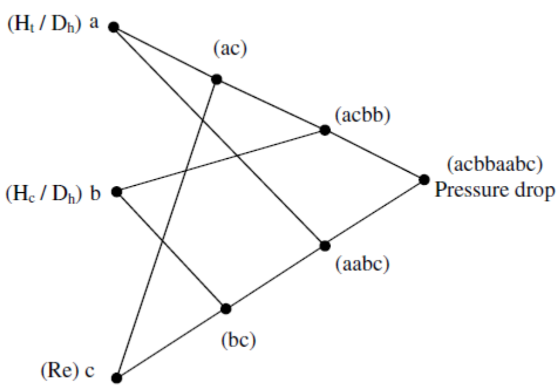

Fig. 6 Evolved structure of generalized GMDH type network for pressure drop

The corresponding polynomial representation for Nu is as follows:

$$\boldsymbol{Y_{12}} = -1.6059 - 85.9982\frac{H_t}{D_h} + 153.8526\frac{H_c}{D_h} - 2.4899\left(\frac{H_t}{D_h}\right)^2 - 53.6971\left(\frac{H_c}{D_h}\right)^2 + 35.8805\frac{H_t}{D_h}.\frac{H_c}{D_h} \tag{23-a}$$

$$\boldsymbol{Y_{23}} = -131.509 + 90.1952\frac{H_c}{D_h} - 0.01159q - 14.7012\left(\frac{H_c}{D_h}\right)^2 - 0.00008326q^2 + 0.03437q.\frac{H_c}{D_h} \tag{23-b}$$

$$\boldsymbol{Y_{34}} = 4.4857 + 0.1108\,q - 0.0005411\,Re - 0.0001179\,q^2 - 0.00000093\,Re^2 + 0.00000191\,Re.q \tag{23-c}$$

$$\boldsymbol{Y_{1223}} = 30.2012 - 2.63069\,Y_{12} + 0.6859\,Y_{23} + 0.05276\,{Y^2}_{12} - 0.004983\,{Y^2}_{23} + 0.02369\,Y_{12}.\,Y_{23} \tag{23-d}$$

$$\boldsymbol{Y_{2334}} = -1.2907 + 0.3696\,Y_{23} + 0.7867\,Y_{34} - 0.01857\,{Y^2}_{23} - 0.04424\,{Y^2}_{34} + 0.05923\,Y_{34}.\,Y_{23} \tag{23-e}$$

$$\boldsymbol{Nu} = 0.1775 + 0.8806\,Y_{1223} + 0.092203\,Y_{2334} - 0.6593\,{Y^2}_{1223} - 0.6382\,{Y^2}_{2334} + 1.2986\,Y_{1223}.\,Y_{2334} \tag{23-f}$$

Similarly, the corresponding polynomial representation of the model for ΔP is in the form of:

$$\boldsymbol{Y'_{13}} = 42.412 + 106.084\frac{H_t}{D_h} - 1.634\,Re - 11.047\left(\frac{H_t}{D_h}\right)^2 + 0.00202\,Re^2 + 0.0251\,Re.\frac{H_t}{D_h} \tag{24-a}$$

$$\boldsymbol{Y'_{23}} = 2333.105 - 1264.87\frac{H_c}{D_h} - 2.254\,Re + 194.907\left(\frac{H_c}{D_h}\right)^2 + 0.00218\,Re^2 + 0.2117\,Re.\frac{H_c}{D_h} \tag{24-b}$$

$$\boldsymbol{Y'_{1322}} = 2158.54 - 0.494\,Y'_{13} - 1394.136\frac{H_c}{D_h} + 0.0082\,{Y'^2}_{13} + 228.925\left(\frac{H_c}{D_h}\right)^2 - 0.1635\frac{H_c}{D_h}.\,Y'_{13} \tag{24-c}$$

$$\boldsymbol{Y'_{1123}} = -1565.476 - 1.4796\,Y'_{23} + 641.691\frac{H_t}{D_h} + 0.0056\,{Y'^2}_{23} - 63.587\left(\frac{H_t}{D_h}\right)^2 + 0.2125\frac{H_t}{D_h}.\,Y'_{23} \tag{24-d}$$

$$\frac{\boldsymbol{\Delta P}}{\boldsymbol{0.5\rho v^2}} = 10.807 - 0.2235\,Y'_{1322} + 0.898\,Y'_{1123} + 0.0064\,{Y'^2}_{1322} + 0.0015\,{Y'^2}_{1123} - 0.0067Y'_{1123}.Y'_{1322} \tag{24-e}$$

The very good behavior of such GMDH type neural network model for Nu is also depicted in Figure 7 both for training and testing data. Such behavior has also been shown for training and testing data of ΔP in Figure 8. It is clearly evident that the evolved GMDH type neural network in terms of simple polynomial equations successfully model and predict the output of testing data that have not been used during the training process.

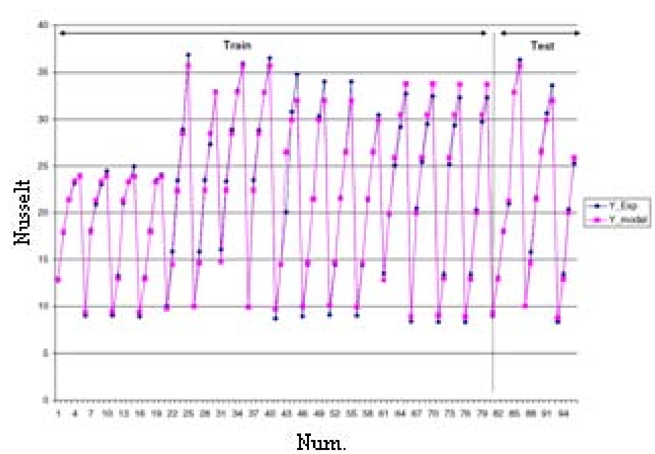

Fig. 7 Variation of Nusselt number with input data.

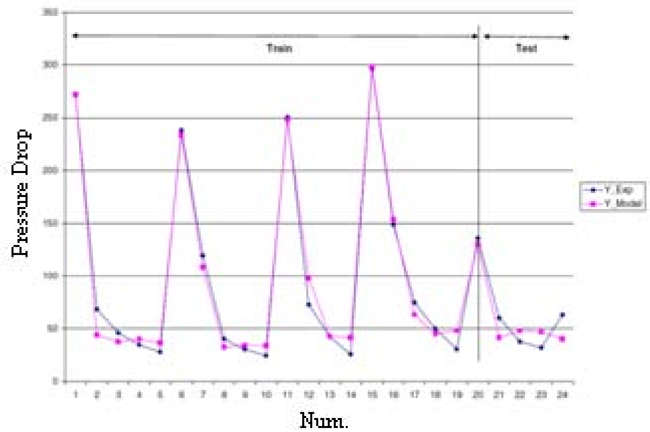

Fig. 8 Variation of pressure drop with input data.

VII. CONCLUSION

In this work the heat transfer in four geometric types of microchannel heat sinks has been investigated. The numerical results have been obtained for thermal resistance and the Nusselt number and showed a good agreement with experimental data. The Nusselt number is found to increase with increasing the aspect ratio. The results also gave the required assurance of using the full Navier-Stokes approach for the microchannels with hydraulic diameters about 100 μm. Genetic algorithms have been successfully used for optimal design of generalized GMDH type neural networks models of heat transfer and flow characteristics of microchannels. Two different polynomial relations for Nusselt number and pressure drop have been found by evolved GS-GMDH type neural networks using some experimentally validated CFD simulations for input–output data of the microchannels. The very good behavior of such polynomials has been shown.

ACKNOWLEDGMENT

The authors wish to express their appreciations to the helpful suggestions and comments of Professor Nader Nariman-Zadeh from Mechanical Department of University of Guilan.

REFERENCES

[1] D.B. Tuckermann, and R.F.W. Pease, “High performance Heat Sinking for VLSI, IEEE Electron,” Dev.Lett.EDL-2, pp. 126-129, 1981.

[2] X.F. Peng, G.P. Peterson, and Wang, B.X., “Heat transfer characteristics of water flowing through microchannels,” Experimental Heat transfer 7, pp. 265-283, 1994.

[3] X.F. Peng, and G.P. Peterson, “Forced convection Heat Transfer of single-phase binary mixture through microchannels,” Experimental thermal and fluid science 12, pp. 98-04, 1996.

[4] B.X. Wang, X.F. Peng, “Experimental Investigation on liquid forced convection heat transfer through microchannels,” International Journal of Heat and Mass Transfer 37 (supple.1), pp. 73-82, 1994.

[5] P. Wilding M. A. Shoffner, and L. J. Kircka., “Manipulation and Flow of Biological Fluids in Straight channels micromachined in Silicon,” Clin.Chem., vol. 40, pp. 43-47, 1994.

[6] X. N. Jiang, Z.Y. Zhou, J. Yao, Y. Li, and X. Y. Ye, “Micro-fluid Flow in Microchannel,” In proc. Transdueers 95, Stockholm, Sweden, June 25-29, pp. 317-320, 1995.

[7] R.J. Philips, “Microchannel heat sinks,” In: Bar-Cohen A, Krausl AD, editors. Advances in thermal modelling of electronic components and systems, vol. 2. New York: ASME Press, 1990 [Chapter 3].

[8] A.G. Federove, R. Viskanta, “Three-dimensional conjugate heat transfer into microchannel heat sink for electronic packaging,” J. Heat Mass Transfer, vol. 43, pp. 399–415, 2000.

[9] A. Weisberg, H.H. Bau, J.N. Zemel, “Analysis of microchannels for integrated cooling,” J. Heat Mass Transfer, Vol. 35, pp. 2465–74, 1992.

[10] Y. CHEN, C. ZHANG, M. SHI, J. WU, “THREE-DIMENSIONAL NUMERICAL SIMULATION OF HEAT AND FLUID FLOW IN NONCIRCULAR MICROCHANNEL HEAT SINKS,” J. HEAT AND MASS TRANSFER. VOL. 36. PP. 917-920, 2009.

[11] E.S. Cho, J.W. Choi, J.S. Yoon, M.S. Kim, “Experimental study on microchannel heat sinks considering mass flow distribution with non-uniform heat flux conditions,” J. Heat and Mass Transfer. Vol. 53. pp. 2159-2168, 2010.

[12] T.C. Hung, W.M. Yan, X.D. Wang, C.Y. Chang, “Heat transfer enhancement in microchannel heat sink using nanofluids,” J. Heat and Mass Transfer. Vol. 55. pp. 2559-2570, 2012.

[13] R.W. Knight, J.S. Goodling, D.J. Hall, “Optimal thermal design of forced convection heat sinks-analytical,” ASME J Electron Pack, Vol. 113, pp. 313–21, 1991.

[14] R.W. Knight, D.J. Hall, J.S. Goodling, R.C. Jeager, “Heat sink optimization with application to microchannels,” J IEEE Trans Components Hydbrids Manuf Technol Vol. 15, pp.832–42, 1992.

[15] H.S. KOU, J.J. LEE, C.W. CHEN, “OPTIMUM THERMAL PERFORMANCE OF MICROCHANNEL HEAT SINK BY ADJUSTING CHANNEL WIDTH AND HEIGHT,” J. COMMUNICATIONS IN HEAT AND MASS TRANSFER. VOL. 35(5), PP. 577-582, 2008.

[16] K.J. Astrom, P. Eykhoff, “System identification, a survey,” Automatica, Vol. 7, pp. 123–62, 1971.

[17] E. Sanchez, T. Shibata, L.A. Zadeh, “Genetic algorithms and fuzzy logic systems,” Riveredge NJ: World Scientific, 1997.

[18] K. Kristinson, G. Dumont, “System identification and control using genetic algorithms,” J. IEEE Trans Syst. Man Cybern, Vol. 22(5), pp. 1033–46, 1992.

[19] J. Koza, “Genetic programming, on the programming of computers by means of natural selection,” Cambridge: MIT Press, MA, 1992.

[20] H. Iba, T. Kuita, H. deGaris, T. Sator, “System identification using structured genetic algorithms,” In: Proceedings of the 5th international conference on genetic algorithms, ICGA’93, USA, 1993.

[21] K. Rodrı´guez-Va´zquez, “Multi-objective evolutionary algorithms in non-linear system identification,” PhD Thesis, Department of AutomaticControl and Systems Engineering, the University of Sheffield, Sheffield, UK, 1999.

[22] C.M. Fonseca, P.J. Fleming, “Nonlinear system identification with multiobjective genetic algorithms,” Proceedings of the 13th World congress of the international federation of automatic control. San Francisco, California: Pergamon Press, pp. 187–92, 1996.

[23] G.P. Liu, V. Kadirkamanathan, “Multi-objective criteria for neural network structure selection and identification of nonlinear systems using genetic algorithms,” IEE Proc Control Theory Appl, Vol. 146(5), pp. 373–82, 1999.

[24] A.G. Ivakhnenko, “Polynomial theory of complex systems,” IEEE Trans Syst Man Cybern, SMC-1, pp. 364–78, 1971.

[25] S.J. Farlow, “Self-organizing method in modeling: GMDH type algorithm,” Marcel: Dekker Inc., 1984.

[26] N. Nariman-Zadeh, A. Darvizeh, G.R. Ahmad-Zadeh, “Hybrid genetic design of GMDH-type neural networks using singular value decomposition for modelling and prediction of the explosive cutting process,” Proc Inst. Mech. Eng. Part B: J Eng Manuf, Vol. 217, pp. 779–90, 2003.

[27] N. Nariman-Zadeh, A. Darvizeh, M.E. Felezi, H. Gharababaei, “Polynomial modeling of explosive compaction process of metallic powders using GMDH-type neural networks and singular value decomposition,” Modell. Simul. Mater Sci. Eng, Vol. 10(6), pp. 727–44, 2002.

[28] K.Salmalian, M.Soleimani, "Modeling and Prediction of Ship Squat using ANFIS and GMDH-type Neural Network", *Wseas Press, Comuters and Simulation in Modern Science*, Vol.5, pp.215-224, 2011.

[29] K.Salmalian, M.Soleimani, S.Rouhi, “Fatigue life Modeling and Prediction of GRP Composites Using Multi-objective Evolutionary Neural Networks”, *International journal of mathematical models and methods in applied sciences*, Vol.6, Issue.1, 2012.

[30] K. Salmalian, N. Nariman-Zadeh, H. Gharababei, H. Haftchenari, and A.Varvani-Farahani," Multi-objective evolutionary optimization of polynomial neural networks for fatigue life modelling and prediction of unidirectional carbon-fibre-reinforced plastics composites," *Journal of Materials: Design and Application,* Vol. 224, No.2, 2010.

[31] K.Salmalian, M.Soleimani, " ANFIS and Neural Network for Modeling and Prediction of Ship Squat in Shallow Waters," *International Journal of Mathematical Models and Methods in Applied Scientifics,* vol.5, No. 4, pp.848-856, 2011.

[32] S.V.Patankar, "Numerical heat transfer and fluid flow," Hemisphere, New York, 1980.