

Comparison of Neural Networks and Fuzzy System for Estimation of Heat Transfer Between Contacting Surfaces

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Abstract: Neural networks can be used in various subjects, such as the discovery of relationships, identification, system modelling, optimization and nonlinear pattern recognition. One of the interesting applications of this algorithm is heat transfer estimation between contacting surfaces. In the current investigation, a comparison study is done for temperature transfer function estimation between contacting surfaces using Group Method of Data Handling (GMDH) neural networks and ANFIS (Adaptive Neuro Fuzzy Inference System) algorithm. Different algorithms are trained and tested by means of input–output data set taken from the experimental study and the inverse solution using the Conjugate Gradient Method (CGM) with the adjoint problem. Eventually, the optimal model has been chosen based on the common error criteria of root mean square error. According to the obtained results among different models, ANFIS with gaussmf membership function has the best algorithm for identification of TCC between two contacting surfaces with 0.1283 error. Also, the inverse method has the lowest error for thermal contact conductance estimation between fixed contacting surfaces with root mean square error of 0.211.

Keywords: ANFIS, Electronic Chipset, Neural Networks, Thermal Contact Conductance (TCC)

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Biographical notes: **Shayan Fathi** is currently a PhD student in mechanical engineering-energy conversion at Islamic Azad University, Central Tehran Branch, Iran. His research interest includes the area of renewable and clean energy particularly solar energy. Furthermore, CFD simulations on natural and forced convection heat transfer and fluid dynamics in turbulent flow and porous media are classified as his concerns. **Mohammad Eftekhari Yazdi** received his PhD in mechanical engineering from Islamic Azad University, Science and Research Branch, his research interest includes the area of CFD simulations on natural convection heat transfer and fluid dynamics in turbulent flow and Nano fluids, heat transfer and entropy generation analyses of turbulent forced convection. **Armen Adamian** received his MSc in mechanical engineering from the University of California (UCLA), and the PhD degree in mechanical engineering from the University of California (UCLA). His research interest includes the area of finite element modelling, numerical optimization techniques, CFD simulations on natural convection heat transfer and fluid dynamics.

1 INTRODUCTION

Exact estimation of thermal contact conductance has become a significant issue in the critical engineering applications such as major fields like cooling purposes in nuclear reactors and spaceship heat transfer management and other fields including electronic packaging, heat exchangers, gas turbines, machine tools, internal combustion engines particularly between exhaust valve and its seat, metal forming and forging applications [1-7]. Because of the undeniable role of thermal contact resistance in various modern industries, many investigations in recent years have been done around this issue. However, the exact computation of TCC between two contacting surfaces is still a major complicated problem. The material and geometry of two contacting solids, the fractions of contacting surface, heat conduction of two contacting materials, the interface medium filling material, contacting pressure, and heat flux are the most important effective parameters on TCC [8-9]. Modelling and system identification is one of the most helpful methods that can be applied in many fields to identify unknown complex systems from input-output data [17]. One of the fields that system identification can be applied, is estimating the temperature transfer function or thermal contact among flat-flat and curvilinear contacts [18].

Thermal contact conductance approximation (TCC) between flat-flat contacts under different conditions and parameters have been investigated broadly during recent years. [4-10]. Different methods have been proposed in order to estimate thermal contact conductance between flat and curvilinear contacts. To illustrate, the lumped parameter method, a transient non-contact manner, has been proposed to determine TCR between two contacting solids [11]. Kumar et al. studied experimentally TCC for cylindrical contacts. Furthermore, a new method according to the Monte-Carlo simulation model, grew for flat conforming surfaces in touch. This method was rectified and developed to estimate TCC among curvilinear surfaces [12].

In addition, Kumar et al. investigated experimental thermal contact conductance in steady state condition among curvilinear contacts using liquid crystal thermography. They presented steady state thermal contact conductance analysis on two solid bodies of brass, carrying flat and curvilinear contact combinations, under variable loading conditions. They used liquid crystal thermography (LCT) to determine the TCC for varieties configurations [13]. Increasingly, McGee et al. studied experimentally thermal resistance of cylinder-flat contacts according to theoretical analysis and experimental investigations of a line-contact model. Also, the effect of contact pressure on thermal contact conductance was investigated [14]. Meanwhile, Asif et

al. studied the relation of TCC for a flat metal contact in a vacuum. Various heat transfer experiments were performed in a vacuum ambience to discover solid spot contact conductance for aforementioned copper, brass, and stainless steel contacts with several surface roughness.

Finally, a particular relation for TCC was offered for different materials [15]. Moreover, a kind of thermal joint resistance modelling for sphere-flat contacts in a vacuum condition was studied by Bahrami. In this regard, a new method was chosen to consider thermal joint resistance and finally a model was suggested which was able to predict the TCR of conforming rough contacts using scale analysis methods [16]. According to the literature review, available theoretical and numerical models are unable to predict thermal contact conductance (TCC) accurately for the majority of the other impressive parameters, so experiments are mostly used for this purpose.

Some scholars have applied traditional back propagation neural (BPN) network for determination of contact heat transfer rate. Based on the outcomes, the LM algorithm supplies the most appropriate performance [19]. Motahari-Nezhad et al. applied an Adaptive Neuro-Fuzzy Inference System (ANFIS) model for prediction of thermal contact conductance between the exhaust valve and its seat. In their paper, the capabilities of the ANFIS method has been studied for estimating heat transfer rate between the exhaust valve and its seat. It is shown that the ANFIS architecture estimates the heat transfer rate between the exhaust valve and its seat very accurately [20].

By literature review it is shown that the Group Method of Data Handling (GMDH) method that uses evolutionary methods for system identification, has not been used for thermal contact identification yet [21-23]. Also, there are a few studies on the application of ANFIS (adaptive neuro fuzzy inference system) for thermal contact estimation. For the first time, a comparison of GMDH and ANFIS methods for TCC estimation between fixed contacts are presented in the present study. In this study, firstly, GMDH method is used to identify a system of multi-input-single-output data pairs of TCC experiment. Then, the ANFIS method is used for the same problem and two algorithms are compared. The primary aim of the study is to estimate the TCC between fixed contacting surfaces using these two algorithms according to the achieved data from the experimental investigation and the inverse method. The structure of GMDH-type networks and ANFIS method is investigated and the most efficient structure is chosen. The temperature of the fixed contacting surfaces is used from an experimental investigation.

Furthermore, the thermal contact conductance is calculated by applying the inverse method. Afterwards, the obtained data is considered as input and output

parameters to the present methods. Firstly, the transient heat conduction problem has been solved by using the continuous-time GMDH network and ANFIS method and the accuracy of the two methods has been compared with each other. The acquired model can be used at the contact surfaces for heat transfer rate estimation.

2 EXPERIMENTAL PROCEDURE

In this study, an experimental setup has been considered and the actual data is taken from a thermal contact conductance experiment conducted by Shojaeefard et al. [27] as an input-output data set. The experimental test setup consists of two contacting rods. The experimental setup is shown in “Fig. 1” and it consists of two test rods, with one of the non-contacting ends located in an ice-water reservoir. Constant heat flux was imposed on the non-contacting end of the other rod. The surfaces of the adjacent ends were brought into contact. The data was measured using thermocouples inserted in the hot specimen and cold specimen. The measured contact surface temperatures of cold (T_{c1}) and hot (T_{c2}) specimen during operation condition is used for determining thermal contact conductance between the two contacting surfaces. The properties of the specimens and detailed description of the experiment can be found in [27].



Fig. 1 The test setup [27].

Also, the schematic of flat-flat contacting surfaces is shown in “Fig. 2”. The inverse heat transfer problem is used to estimate the TCC between surfaces. Experimental data of contacting surfaces temperatures which has been taken by thermocouples inserted in two contacting specimens are considered as input data for simulation. Figure 3 shows the contacting surface temperatures [27].

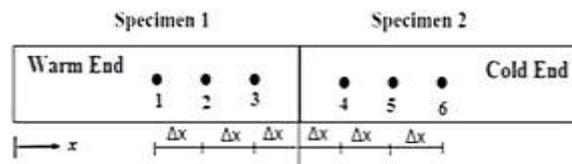


Fig. 2 Schematic of flat-flat contacting surfaces [27].

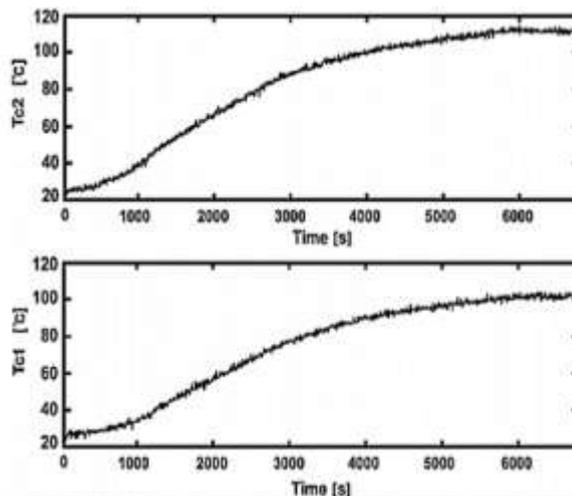


Fig. 3 Contacting surface temperatures [27].

3 PROBLEM FORMULATION

In this study, as it was mentioned, the TCC between fixed contacting surfaces is estimated using GMDH and ANFIS algorithm based on the data calculated from the inverse method. As it has been shown in “Fig. 2”, in the present study, the basic geometry of the problem and the coordinate system for the one dimensional problem is assumed. Two contacting surfaces are in contact with a TCC of $h_c(t)$ at the interface. Constant temperatures and constant heat flux are governed at one side of the down sample and at the end of the upper specimen respectively [27]. Heat transfer equations between two contacting specimens are expressed as follows:
For upper specimen:

$$\frac{\partial^2 T_{up}}{\partial x^2} = \frac{1}{\alpha_{up}} \frac{\partial T_{up}}{\partial t} \text{ in } L_1 < x < L_2 \text{ for } t > 0; \frac{\partial^2 T_{up}}{\partial x^2} = \frac{1}{\alpha_{up}} \frac{\partial T_{up}}{\partial t} \text{ in } L_1 < x < L_2 \text{ for } t > 0; \frac{\partial^2 T_{up}}{\partial x^2} = \frac{1}{\alpha_{up}} \frac{\partial T_{up}}{\partial t} \text{ in } L_1 < x < L_2 \text{ for } t > 0; \quad (1)$$

$$k_x \frac{\partial T_{up}}{\partial x} = q \text{ at } x = L_2 \text{ for } t > 0; \quad (2)$$

$$k_{up} \frac{\partial T_{up}}{\partial x} = h_c(t) [T_{up} - T_{down}] \text{ at } x = L_1 \text{ for } t > 0; \quad (3)$$

$$T_{up}(x, 0) = T_i \text{ } 0 < x < L_1 \quad (4)$$

For down specimen:

$$\frac{\partial^2 T_{down}}{\partial x^2} = \frac{1}{\alpha_{down}} \frac{\partial T_{down}}{\partial t} \text{ in } 0 < x < L_1 \text{ for } t > 0 \quad (5)$$

$$T_{down} = T_0 \text{ at } x = 0 \text{ for } t > 0 \quad (6)$$

$$k_{down} \frac{\partial T_{down}}{\partial x} = h_c(t) [T_{up} - T_{down}] \text{ at } x = L_1 \text{ for } t > 0 \quad (7)$$

$$T_{down}(x, 0) = T_i \quad (8)$$

3.1. Inverse Method

In the inverse method, all parameters except thermal contact conductance, h_c , are known in this problem. The temperature of the considered points in the two mentioned samples will be calculated by solving the inverse problem. Figure 2 shows the location of thermocouples inserted in the two specimens. The measurements are done at different times i ($i=1, 2, \dots, I$). Suppose N_1 and N_2 are the numbers of thermocouples which are located on two specimens. Then, the temperatures are calculated as:

$$Y_{1j}(t) = Y_{1j}, j = 1, 2, 3, \dots, N_1 \quad (9)$$

$$Y_{2k}(t) = Y_{2k}, k = 1, 2, 3, \dots, N_2 \quad (10)$$

Considering the inverse method, it is regarded that the previous data about the TCC and $h_c(t)$ amounts have not been clarified. Consequently, the amount of $h_c(t)$ in a period of time is desired. Also, it is supposed that $h_c(t)$ belongs to the Hilbert space of square integrable functions as:

$$\int_0^{t_f} [h_c(t)]^2 dt < \infty \quad (11)$$

The inverse method is solved upon minimization of the Equation (12).

$$S[h_c(t)] = \sum_{j=1}^{N_1} (T_{1j} - Y_{1j})^2 + \sum_{k=1}^{N_2} (T_{2k} - Y_{2k})^2 \quad (12)$$

Where T_{1j} and T_{2k} represent the approximated temperatures in the mentioned samples, respectively. The details of the conjugate gradient method with the Adjoint problem is available in Ref. [24-26].

3.2. The Extrapolation Method

This method is applied for inverse method validation which is used to measure TCC according to the temperature difference and heat flux between contacting surfaces. The TCC in this method is calculated as:

$$h_c = \frac{q}{\Delta T} \quad (13)$$

Where q represents the heat fluxes average among two mentioned samples and also ΔT presents the temperature drop in the interface that is measured by extrapolation of temperature profiles of each contact surfaces [27].

3.3. GMDH-type Networks

Neural networks are defined as a stage of generalized nonlinear models which affected by numerous investigations of the human brain. One of the most important points of the mentioned method is that it will be able to estimate all nonlinear functions to any degrees of accuracy with a proper number of hidden units [28]. The GMDH-type neural networks which include multilayered neural network architectures [29-31] are able to form the neural network design spontaneously by applying a heuristic self-organization method and the main parameters like, number of layers, useful input variables, number of neurons in a hidden layer and optimized design of the neurons in a hidden layer [32-34]. Heuristic self-organization method is categorized as an evolutionary calculation.

GMDH algorithm has been introduced by Ivakhnenko [35-36] for modelling complex systems as a learning method. It has a multi-layered and forwards network structure. Each layer is composed of one or more processor units, which each has two inputs and one output. The units that play the role of model components are considered in the form of a 2-D polynomial as followings:

$$z = a_0 + a_1 x_1 + a_2 x_2 + a_3 x_1 x_2 + a_4 x_1^2 + a_5 x_2^2 \quad (14)$$

x_1 and x_2 are inputs, z is output, a_i are the coefficients. The structure of a 3 layers GMDH model including 4-inputs has been shown in “Fig. 4”.

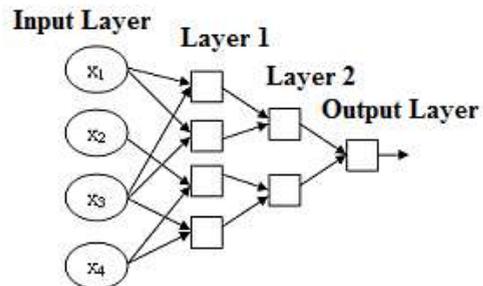


Fig. 4 The neural networks structure of a 3-layer GMDH model.

To start with the GMDH algorithm, two problems exist: 1- recognizing the relationship between the output variables based on the input variables of x_i .

2- The prediction of y for known values of x_i . In another word, we need to recognize the relationship between the variables (modelling). Then, the prediction of future target variables according to the model will be possible.

The identification problem is described as a method to achieve a function \hat{f} which is able to be used approximately rather actual one, f , in order to predict output \hat{y} for a given input vector $X = (x_1, x_2, x_3, \dots, x_n)$ as close as possible to its real output y [37-39]. GMDH algorithm is a process for the production of a higher order polynomial namely Volterra functional series presented as follows:

$$y = a_0 + \sum_{i=1}^m a_i x_i + \sum_{i=1}^m \sum_{j=1}^m a_{ij} x_i x_j + \sum_{i=1}^m \sum_{j=1}^m \sum_{k=1}^m a_{ijk} x_i x_j x_k + K \tag{15}$$

This complex discrete form of the Volterra function is represented by quadratic polynomials as follows:

$$\hat{y} = G(x_i, x_j) = a_0 + a_1 x_i + a_2 x_j + a_3 x_i^2 + a_4 x_j^2 + a_5 x_i x_j \tag{16}$$

Where a_i are calculated by regression equations as the discrepancy between the real output, y , and measured output, \hat{y} , for each of x_i and x_j as input variables become minimized [34-36]. As a reformulation, each quadratic function coefficients are measured to fit the output in the entire set of input-output data. It is shown as:

$$r^2 = \frac{\sum_{i=1}^M (y_i - \hat{y})^2}{\sum_{i=1}^M y_i^2} \rightarrow \min. \tag{17}$$

By GMDH algorithm method, the whole binary compounds have been formed from 'n' input variables. Additionally, unknown coefficients of whole neurons are achieved using the least squares method. Consequently, $\binom{n}{2} = \frac{n(n-1)}{2}$ neurons are made in the second layer that it can be demonstrated as [34-36]:

$$\{(y_i, x_{ip}, x_{iq}) \mid (i = 1, 2, \dots, M) \ \& \ p, q \in (1, 2, \dots, M)\} \tag{18}$$

Using from the quadratic function of Eq. (18) for all of the M data triples, these equations will be represented in the matrix form as [34-36]:

$$Aa = Y \tag{19}$$

Where 'a' is unknown coefficients of the quadratic equation, such as [34-36]:

$$a = \{a_0, a_1, \dots, a_5\} \tag{20}$$

And:

$$Y = \{y_1, y_2, y_3, \dots, y_M\}^T \tag{21}$$

Where Y is vector of output's value. Based on amount

of input vectors, it is easily visible that:

$$A = \begin{bmatrix} 1 & x_{1p} & x_{1q} & x_{1p}^2 & x_{1q}^2 & x_{1p}x_{1q} \\ 1 & x_{2p} & x_{2q} & x_{2p}^2 & x_{2q}^2 & x_{2p}x_{2q} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & x_{Mp} & x_{Mq} & x_{Mp}^2 & x_{Mq}^2 & x_{Mp}x_{Mq} \end{bmatrix} \tag{22}$$

Using the method of least squares, Eq. (19) will be solved as [34-38]:

$$a = (A^T A)^{-1} A^T Y \tag{23}$$

Two methods are used for solving equation (19), which are Solving Normal Equations (SNE) method and Singular Value Decomposition (SVD) method. In the SNE method, by solving normal equations, the vector of the optimal coefficient of quadratic polynomials in Eq. (19) is calculated as [34-38]:

$$a = (A^T A)^{-1} A^T Y \tag{24}$$

In SVD method, matrix $A \in R^{N \times 6}$ is decomposed to the product of three matrices: column orthogonal matrix of $U \in R^{N \times 6}$, the diagonal matrix of $W \in R^{6 \times 6}$ with non-negative elements, and the orthogonal matrix of $V \in R^{6 \times 6}$ so that:

$$A = U \cdot W \cdot V^T \tag{25}$$

Then the vector of optimized coefficients 'a' in equation (20) is calculated as

$$a = V \cdot \left[\text{diag} \left(\frac{1}{W_j} \right) \right] \cdot U^T \cdot Y \tag{26}$$

The use of SVD in the structure of the GMDH algorithm is a factor to optimize the algorithm and enhance the performance of GMDH method [31-33].

3.3.1. Designing the structure of GMDH-type networks

In the design of GMDH-type network, target is to prevent the growth of divergence related to the network and to link the network structure to one or more numeric parameters which by changing of them, the network structure will also be changed. Generally, in the design of various structures of networks, two general issues are considered:

- 1- Finding the number of layers and number of neurons in each layer and providing a way to control and picking them up.
- 2- Finding communication patterns of neurons with each other and providing a way to create an optimal connection between them.

Therefore, considering these two issues, we propose an evolutionary design of neural networks as described following:

• **Pre-specified-network (PSD) method**

In this method, the main parameters of the network structure, including the layer and neuron numbers are predetermined directly and completely optional with no limits. The plan of this method is to select the main parameters repeatedly and to create different structures, so that the optimal parameters be identified. In fact, the performance of this method is somewhat similar to the practice of trial and error that the ideal structure of the network is identified as the result of this practice. The details of this method can be found in [34-36]. Structure of GMDH-type network obtained by PSD is shown in “Fig. 5”.

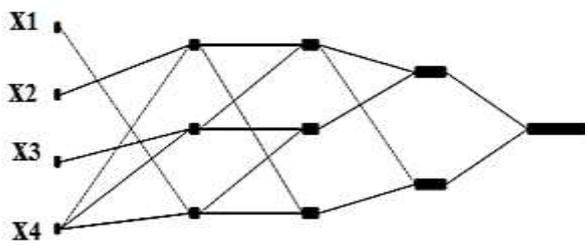


Fig. 5 Structure of GMDH-type network obtained by PSD.

• **Design of Neural Network by Genetic Algorithm**

In this method, a genetic algorithm is used for neural network convergence. Genetic algorithms (GAs) are more efficient than traditional gradient methods and are utilized to train neural networks with coefficients and associated weights. Classical GMDH algorithm can be in the form of a set of neurons, whereby in each layer various neuron pairs are connected and associated with a quadratic polynomial, thus creating new neurons in the next layer. Therefore, it is possible to produce a simple and novel encoding scheme applicable to the evolutionary design of the generalized structure GMDH (GS-GMDH) where the connectivity configuration is not limited to adjacent layers. GS-GMDH encoding scheme involves GA and two objective functions, i.e. Training Error (TE) and Prediction Error (PE), and presents accurate solutions. This kind of GMDH must exhibit the ability to specify different sizes and lengths of such neural networks. GS-GMDH is summarized below. Neuron 14 in the first hidden layer is connected to the output layer directly and passes to the second layer. Hence, the output layer neuron is denoted by 12231414 (with 14 twice). In fact, a neuron 1223 in the second hidden layer is used to induce output neuron 12231414 by constructing a virtual neuron 1414 created in the second hidden layer (“Fig. 6”).

If a neuron traverses many adjacent layers and connects to another neuron in the next second, third, fourth or following hidden layers, the above iteration takes place. The number of neuron iterations depends on the number

of hidden layers traversed, n^h , which is computed as 2^{n^h} . It is also notable that chromosome 1212 2323 (not the same as chromosome 1212 1323) is not valid and should be rewritten as 1223. The crossover and mutation genetic operators are utilized to induce two offsprings from the parents.

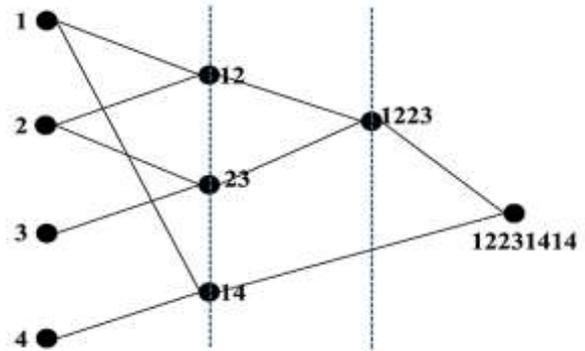


Fig. 6 GS-GMDH network chromosome structure.

The crossover of two chosen individuals, substitutes two chromosomes’ tails by a random point selected according to “Fig. 7”. The building block information of GS-GMDH can be substituted by crossovers, as seen in “Fig. 8”. Different length of chromosomes created via such crossover operation lead to varying GS-GMDH network structure sizes. The population diversity is related to the mutation operation, which is easily substituted by different chromosome genes to other possible symbols, e.g. 12231414 to 12233414. These operations are repeated until a valid chromosome is created.

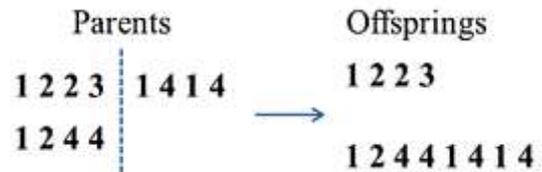


Fig. 7 Crossover operation of two individuals in the GS-GMDH model.

In the evolutionary design method, the limits caused by setting the error as the criterion for determining network structure is removed and the same chance to all neurons for establishing the neural network is considered. In fact, there will not be any restrictions on the establishment of the network and all operations will be done randomly. The only two criteria of the neuron numbers in the network and the output error of the network are considered for selection. Combining the genetic algorithm into the GMDH-type neural networks structure begins with organizing each network to a series of alphabetical numerals linked together. The fitness, (ϕ), of each whole series of representative numerals that shows a GMDH-type neural network is measured as:

$$\Phi=1/E \tag{27}$$

Where E, the mean square of error (MSE), is minimized through the progressive process by increasing the fitness ϕ . The progressive process begins with accidentally creating an initial population of symbolic numerals each as a desired answer. Afterwards, the whole community of symbolic numerals improves regularly. Figures 7 and 8 show the structure of GMDH-type network obtained by Genetic>SNE and Genetic>SVD, respectively [35-37].

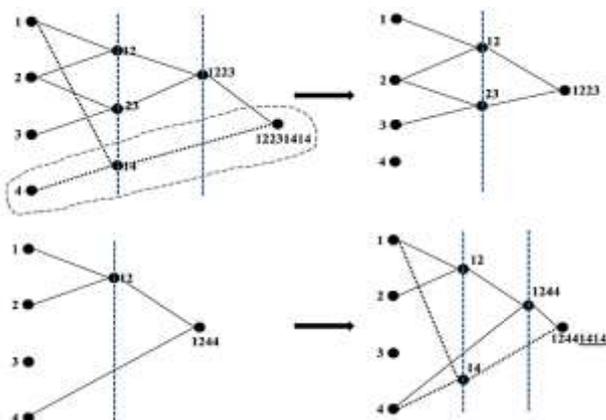


Fig. 8 Crossover operation in two GS-GMDH networks.

3.4. ANFIS Network

In neuro-fuzzy models, a network structure comprises fuzzy if-then rules are used to represent systems and these models apply algorithms from the area of neural networks. The adaptive network based fuzzy inference system, which is a fuzzy inference system and first proposed by Jang [43], produces a Fuzzy Inference System (FIS) by means of a given input/output data set. The membership function parameters of FIS are adjusted by either a back-propagation algorithm solely, or using a combination of back-propagation algorithm and a method of least squares type [44]. For describing the ANFIS architecture, the system with two inputs (x_1 and x_2), two fuzzy if then rules based on Takagi and Sugeno’s type [44] and one output (y) are considered as follows:

Rule 1: If (x_1 is A_1) and (x_2 is B_1) then $f_1 = p_1x_1 + q_1x_2 + r_1$ (28)

Rule 2: If (x_1 is A_2) and (x_2 is B_2) then $f_2 = p_2x_1 + q_2x_2 + r_2$ (29)

Where A and B are the fuzzy sets, p, q and r are consequent parameters of the model determined during the training process. The architecture of ANFIS is shown in “Fig. 9”.

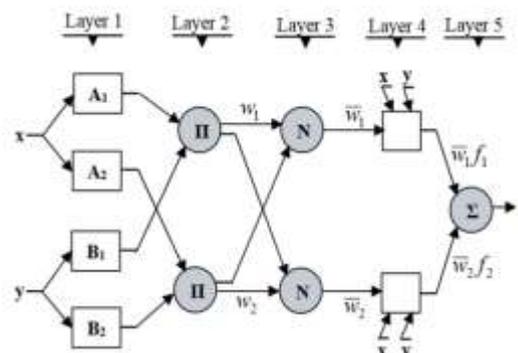


Fig. 9 Structure of ANFIS.

It is constructed from 5 layers. The first layer is the input layer and contains adaptive nodes and every node in this layer is a square node. Every node in the second layer is a fixed square node demonstrated by a circle and labeled Π which multiplies the input signals and produces the output. Every node in layer 3 is a fixed node, marked by a square and labeled N. The i^{th} node calculates the ratio of the i^{th} rule’s firing strength to the sum of all rules’ firing strengths [45]. The consequence is produced in layer 4. Every node in this layer is an adaptive square node. The fifth layer is the summation layer. It comprises a single fixed node labeled Σ , which sums up all of the input signals and computes the overall output.

3.4.1. Membership Functions

A Membership Function (MF) is a curve that determines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. Different membership functions are constructed based on several basic functions: piecewise linear functions, the Gaussian distribution function, the sigmoid curve, and quadratic and cubic polynomial curves. Different input membership functions for ANFIS and their purpose that have been used in this study are shown in “Fig. 10” and also are tabulated in “Table 1” [27-28].

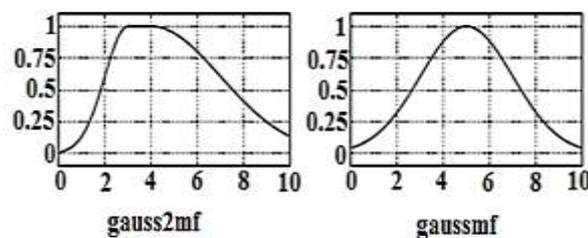


Fig. 10 Membership functions: gauss2mf and gaussmf.

Table 1 Input membership functions	
Membership Functions	Purpose
gauss2mf	Two-sided Gaussian curve membership function.
gaussmf	Gaussian curve membership function.

4 RESULTS AND DISCUSSION

In the present study, the thermal contact conductance approximation between two fixed contacting surfaces using GMDH-type neural network and ANFIS method with respect to the input data which are taken by using the inverse method has been investigated. Two cases have been considered for these purposes. In both cases, using the experimental data, the temperatures of four specified points in the hot specimen are considered as input. In case one, using the experimental, the temperature of one point on cold specimen is considered as output (“Fig. 3”). Then, the network is trained based on these set of input-output data and the best algorithm is selected based on the root mean square error. In case 2, using the experimental data and the inverse method, TCC of two contacting specimens is calculated and considered as the output parameter. Again, the network is trained and the best algorithm is chosen according to the achieved results.

The performance of each two algorithms has been compared according to the root mean square error. A GMDH-type neural network with Genetic and PSD structure is applied in this regard. Also, the ANFIS algorithm with gaussmf and gauss2mf membership functions are studied. The inverse method was used for determining the TCC by applying the contact surface temperatures of two fixed contacts (“Fig. 3”). The experimental data and the inverse method are used to calculate the TCC of two contacting specimens. Then, for case 2 the calculated TCC is considered as the output parameter. Afterwards, for case 2, the GMDH network and ANFIS method are trained using the input-output data. The algorithms are designed and the most appropriate algorithm is chosen according to the achieved results.

To determine the integrity and reliability of the proposed models for estimating TCC and to evaluate the performance of GMDH network and ANFIS method, Root Mean Square Error (RMSE) is used, and expressed as follows [38–42]:

$$RMSE = \sqrt{\frac{\sum_{i=0}^M (Y_{model} - Y_{exp})^2}{M}} \tag{30}$$

Where M is the number of observations, Y_{model} and Y_{exp} are the modelled and experimental data respectively. “Tables 2 & 3” tabulate the prediction error of different methods for case 1 and 2. As it has been shown, the ANFIS algorithm with gaussmf membership function produces the lowest error compared with other methods for fixed contacts and the performance of ANFIS algorithm with gaussmf membership function is remarkably more powerful than other methods by regarding the root mean squares of errors related to different methods. So, it is precise enough to contact

heat transfer rate estimation between fixed contacts and it is reliable enough to be chosen as the most accurate algorithm for thermal contact prediction among these types of contacts.

Table 2 The errors and prediction accuracy of TCC for different methods for the fixed contacts in case 1

Structure	RSME
GMDH>Genetic	0.2794
GMDH>PSD	0.2648
ANFIS>gaussmf	0.1283
ANFIS>gauss2mf	0.2983

Table 3 The errors and prediction accuracy for TCC for different methods for the fixed contacts in case 2

Structure	RSME
GMDH>Genetic	0.3441
GMDH>PSD	0.3007
ANFIS>gaussmf	0.2676
ANFIS>gauss2mf	0.3932

The behaviour of GMDH-type and ANFIS network when they were used for modelling experimental data in conjunction with different algorithms for case 1 is depicted in “Fig. 11”.

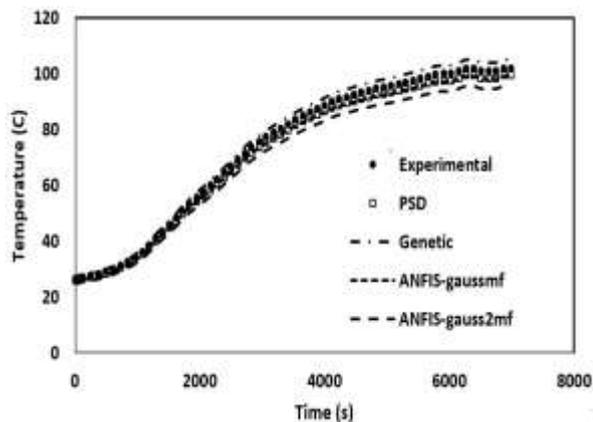


Fig. 11 Comparison of Experimental and Modelled data obtained by different algorithms for fixed contacts for case 1.

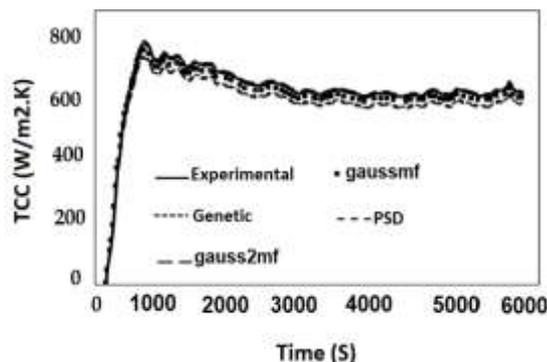


Fig. 12 Comparison of Actual and Modelled data obtained by different algorithms for fixed contacts for case 2.

It can be seen that the ANFIS algorithm produces the best results. Also, the behaviour of GMDH-type and ANFIS network when it was used for modelling of the experimental data in conjunction with different algorithms for case 2 is depicted in “Fig. 12”. This figures also show ANFIS proper accuracy with gaussmf membership function.

Figure 13 shows root mean square error changes based on time in inverse method and extrapolation method in the prediction of thermal contact for fixed contacts. Also, the root mean square error which was achieved from two variant methods is shown in Table 4. According to “Fig. 13” and “Table 4”, the error of the inverse method and extrapolation method for thermal contact prediction between fixed are 0.211 and 0.283, respectively. The rate of errors shows that the inverse method produces less error than the extrapolation method in TCC estimation between fixed contacts. Also, from “Fig. 13” it can be seen that the error for both inverse and extrapolation methods increases over time.

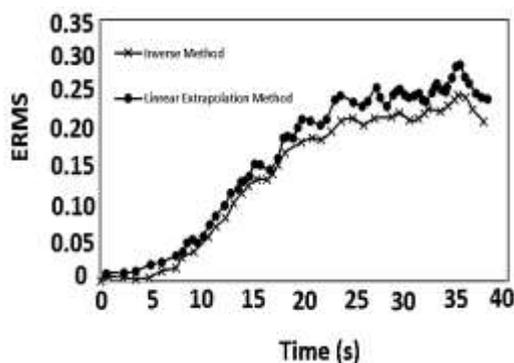


Fig. 13 The variation of RMSE versus time for different methods for fixed contact.

Table 4 The root mean square error obtained from two different method

Method	RMSE error
Inverse Method (CGM method)	0.211
Linear Extrapolation	0.283

5 CONCLUSION

Identification and prediction of TCC between fixed contacts are two of the most important and crucial issues to control the temperature rate in many industrial applications. Because of this fact, it seems providing an appropriate and accurate model with the ability to estimate contact heat transfer rate between fixed contacts is necessary and required. In the present study, firstly, the TCC rate has been calculated by using the inverse method. Then, the GMDH and ANFIS models were presented to estimate the TCC between fixed contacts acquired by benefiting empirical data on the

geometries of fixed contacting surfaces. Two different models of GMDH networks and two different membership functions of ANFIS algorithm were suggested to predict the contact heat transfer between fixed contacts. Two different cases also have been considered. In both cases, using the experimental, the temperature of two points on the hot specimen is considered as input. In case 1, the temperature of the cold specimen is considered as the algorithm output. For case 2, TCC obtained by inverse method is considered as output. According to the results, the inverse method is accurate enough to predict TCC between fixed contacts with the root mean square error of 0.211. Also, it has been shown that among the different models of GMDH and ANFIS algorithms, ANFIS algorithm with gaussmf membership function, makes the best algorithm for TCC identification in fixed contacting surfaces. Meanwhile, the computed Root Mean Square Error (RMSE) of the ANFIS algorithm obtained by gaussmf membership function compared with the experimental results for fixed contact for case 1 and case 2 are 0.1283 and 0.2676, respectively. ANFIS network is an accurate and powerful tool to identify the contact heat transfer between fixed contacts. The proposed algorithm can be used as an accurate method for the TCC approximation between fixed contacts.

NOMENCLATURE

- CGM : Conjugate gradient method
- h_c : Thermal contact conductance
- k : Thermal conductivity
- q : Heat flux
- T : Temperature
- R : Result function
- x : Cartesian spatial coordinate
- RMSE : Root mean square error
- L : Length
- t : Time
- Y : Measured temperatures
- T_0 : Constant temperature at $x = 0$ (K)
- T_i : Initial temperature (K)
- α : Thermal diffusivity
- β : Search step size
- γ : Conjugation coefficient
- λ : Lagrange multiplier satisfying the Adjoint problem

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