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Thermodynamic analysis of two-shaft radial gas turbine data using artificial neural network method

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Abstract

In the present research, an artificial neural network was designed and conducted to thermodynamically analyze performance variables of two-shaft radial flow gas turbine model GT185. To do this, firstly the needed tests were conducted at different operating conditions and the essential variables like temperature, pressure, rotational speed, mass flow rate which totaled 17 inputs were recorded. Then, using the relations regarding radial flow turbines and the laboratory results, performance variables including compressor, gas turbine and free turbine power and efficiency and finally the cycle heat efficiency were calculated. After calculation of these variables for all laboratory data, a neural network was designed and tested using Matlab software toolbox in order to facilitate the obtaining of performance variables in different operating conditions. In this network, highest errors absolute values of training, verification and testing data were 0.32, 0.86 and 1.39 respectively. Error value of the produced function of sample laboratory results and manual calculations was less than 0.1%

Keywords: Laboratory study; Radial flow gas turbine; Cycle heat efficiency.

1- Introduction

Gas turbine is a rotational internal combustion engine from the family of turbo machines in which the airplane jet engine is recognized in public view as its most widespread application. Gas turbine is a rotary machine which operates using the energy of combustion exhaust gases. Increasing application of gas turbines in different industries specially petroleum and electronics industries in order to operate for example huge pumps of oil and gas pipelines, supplying the power needed for factories and specific areas far away from the power network is very conspicuous and considerable. Gas turbines are divided into two types of axial and radial flow gas turbines. Radial flow gas turbine is regarded as a power generating machine and has a wide range of application, including small turbochargers, small power generating units like airplane and small industrial gas turbine. The application of this type of turbine is in the range of high head and low flow rate. Radial flow turbine has some advantages over axial ones such as low production cost and lower susceptibility in parts distance compared to axial turbine.

In 1976, Wallace et al. [1] used one-dimensional analysis with experimental models of loss to calculate the primary dimensions of the rotor. In this model, the flow in all parts of turbine such as inlet volute, inlet nozzle, rotor and outlet is taken into account. Losses considered in fixed parts were only due to friction and in motion parts besides friction, clearance and disk friction. Continuity, momentum, energy and entropy equations were solved. The authors stated that the expected efficiencies were well adapted to laboratory results.

Studies on one-dimensional design analysis method were also presented by other researchers such as X. Qiu et al. [2], Whitfield & Baines [3] and Ebaid [4].

In 1997, Spence et al. [5] studied the strike losses in a radial flow turbine rotor in laboratory conditions. They drew a graph of the relations between loss and strike angle in the rotor inlet. The primary cause of efficiency decrease in the out of plan conditions was deviation of strike angle from optimum angle. As a result of this analysis, using negative strike angle as the optimum angle was testified.

Baines & Yeo [6] measured internal details of flow in the twin-entry radial turbine using laser speedometer.

Capobianco & Gambarotta [7] studied the experimental performance of twin-entry radial turbine under the conditions of complete and partial admission in the continuous and pulsating case. The study results showed that the efficiency of twin-entry turbine was lower than single-entry turbine and were compatible with other researchers' findings. The results also showed that the mass flow rate and second inlet efficiency which located farther from the center, was higher than the first inlet in complete and partial admission cases.

Ghasemi et al. [8] analytically studied the performance of twin-entry radial turbine under the conditions of transient and partial admission. The model used in this study was to predict the value of one-dimensional efficiency. The Loss coefficients were calculated taking into account the friction, clearance value and blade load. The results showed that unlike single-entry turbine in which the flow is symmetrical, this assumption was not true in twin-entry turbine. Hence, a modified coefficient was calculated for the radial velocity profile on rotor. Finally, using previous assumptions a computation model was developed and its results were compared to laboratory results and showed a good match between them.

Aghaali & Hajilouy [9] experimentally and analytically studies twin-entry radial turbine with asymmetric casing under the conditions of complete and partial admission. The method used was based on the prediction of one-dimensional efficiency developed for partial admission conditions. Laboratory studies were conducted using an apparatus designed for this purpose. The studies were done for a wide range of velocities. The comparison of laboratory and calculation results showed a good adaptation. Also, the results showed that the highest efficiency value occurred when the shroud mass flow rate exceeded hub mass flow rate.

Baines [10] presented a comprehensive method for designing radial turbine. The method was that the designer at first selects the values of stage loading and flow coefficients in a suitable range. After continual selection of these parameters, design point for the highest efficiency condition is determined. He also used computational fluid dynamic method in designing. He believed that even in weak computational network, the flow characteristics in rotor can be predicted using this analytical method.

Zanganeh [11] used a reverse method for designing impeller. After determining the distribution type of side component of average velocity parameter along the impeller using flow analysis software and solving 3D equations of infrasonic compressible flow, the 3D form of the blade will be obtained.

Huntsman et al. [12] designed and tested a radial flow turbine for a gas generator. The analysis results on the design were depicted as flow lines curves in 2D blade to blade case using completely 3D viscous and inviscid computational methods.

Mrša [13] proposed an optimum designing method for tongue and wicket angle of the turbine inlet. In this method, the potential flow is analyzed at the contact range to circular flows. Intensity of circulation is calculated using least squares. The results of numerical analysis showed that the outlet flow angles in the turbine designed according to the above-mentioned optimum method, better acted compared to other non-optimum methods.

Asgari et al. [14] studied an artificial neural network in order to analyze a single shaft gas turbine. They created a comprehensive computer code for this network. Their code included different training functions, different numbers of neurons and also different transfer functions for hidden layers and network output. They showed that ‘trainlm’ training function had a high ability to minimize the error compared to other training functions.

Feng et al. [15] aerothermodynamically designed and numerically assimilated the rotor of a small 100 KW radial flow turbine. They studied the effect of velocity to outlet flow coefficient ratio on the aerodynamic performance and concluded that when the mass flow rate is high, in order to decrease the rotor height in the outlet the velocity ratio should be selected high. They also concluded that for this turbine, the best strike angle of flow in the turbine inlet is a 32 degrees angle to the radial direction.

Daabo et al. [16] conducted a numerical study on the application of small axial and radial turbines in solar conditioning systems operated on Brayton Cycle. The assimilated turbines in this study were small size turbines of 5 to 50 KW power. The results showed that the two-stage axial turbine efficiency was higher than its designed value. Inversely, one-stage radial turbine showed a higher output power in similar conditions.

D'souza et al. [17] studied the performance of an ultra-micro scale radial gas turbine through an experimental investigation, through a series of transient and steady state tests. From the steady state tests, a maximum electrical and turbine power of 4 and 15 W were attained at a rotational speed of 57,000 and 69,000 rpm. Also, a thermal cyclic efficiency of 18.6% was attained, and therefore the study has successfully investigated the performance of the turbine.

Yuan et al. [18] examined the performance of radial turbines with the He-Xe mixtures, helium, argon and air in their paper. The independent or combined effects of the flow Euler number (Eu), Reynolds number (Re) and inflow velocity on flow similarity are discussed based on flat-plate flow.

Due to the wide spread use of radial flow turbines in different industries, it is essential for those industries to acquire technical knowledge of their design and behavior precise analysis. In spite of this necessity, since the technical knowledge of radial turbine designing is classified as confidential information of the companies, so this knowledge is not simply accessible. On the other hand, it is important and necessary to obtain a correct understanding of efficiency and output power changes of radial turbine due to the changes of operating conditions. It should be noted that all the operating conditions cannot be studied in laboratory environment; besides of laboratory limitations, the costs of such experiments would be high. In this study, we have endeavored to use laboratory data and predictive methods of efficiency and output power in order to obtain a good understanding of radial flow turbine behavior while reducing time and costs. Researchers have always tried to use methods to get a correct prediction of instruments performance characteristics, while reducing laboratory costs; therefore, mathematical modeling between laboratory input and output data and exploration of logical relations among these data have always been considered so that it can be used to develop and predict behavior. Finding such models is very difficult. Recently, using emerging methods of artificial intelligence acquired much attention so to be used in such cases. One of the most popular and best methods is neural network which has the ability to relate different data and model complicated relations.

2-Research Method

2-1- Experiment apparatus

Two shaft radial gas turbine model GT185 manufactured by TecQuipment company, is a low price apparatus which is used to study the efficiency and characteristics of turbine engines. Fig. 1 shows the apparatus.

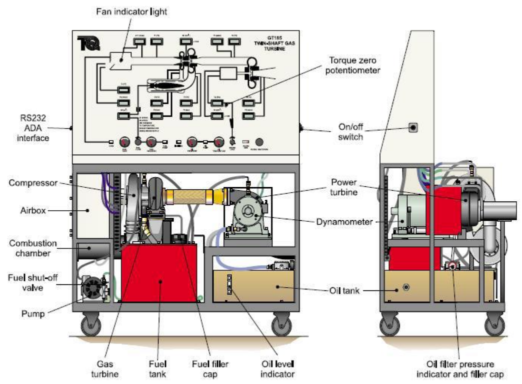

Fig. 1 Schematic form of radial turbine [19]

Gas turbines used in thermal engines all have approximately the same cycle which consists of three processes of compression, combustion and expansion. The air is injected into the system through a metering nozzle; then, is compressed with the ratio of 2.2 to 1 by a centrifuge compressor which is capable of rotating with a speed of 90000 rpm. The outlet air then enters into the combustion chamber with lower velocity and after mixing with fuel with the ratio of 70 to 1, combustion takes place. As a result, a gas with high temperature and velocity is produced which enters the turbine to provide enough moving force for the compressor. The remaining gas of high velocity is guided toward a free turbine that moves a dynamometer, which is considered a mechanical output load.

2-2- Data gathering method in laboratory

Data gathering conditions are as follows: with one turbine speed kept constant, the other turbine speed is changed and after the indicators of the apparatus showed stable values, data recording is done.

This apparatus uses air as the needed fluid. The air may have different characteristics depending on the environment. So, all the computations done in this section should be corrected and the ‘c’ subscript is used for this purpose.

Modified base unit:

$$T_a = t_a + 273.16(K) \qquad (1)$$

where T_a is the environment temperature. In general, the temperature is calculated using the following formula:

$$T_{XC} = (t_a + 273.16)\left(\frac{288.16}{T_a}\right) \qquad (2)$$

where T_{XC} is the corrected temperature.

Pressure in mbar is calculated using the following formula:

$$P_{XC} = (P_X + P_a)\left(\frac{1013.3}{P_a}\right) \qquad (3)$$

If a comparison is done between recorded data and previous data which were recorded in different environment temperature and pressure, it is necessary to modify all the data according to a common standard. If there is no need to compare data recorded on a specific day with another date and if only that data is needed, then modification of data would not be necessary.

It should be noted that all temperatures are measured in degrees centigrade and must be converted to degrees Kelvin. It is also notable that P_a and P_3 values are in bar while other pressures are in millibar.

In this research, the conducted experiments consist of 78 cases of different rotating speeds. All the 78 data series were divided in three classes as follows:

1- Second turbine speed is constant and coupled to dynamometer, including 30 data series;
2- First turbine speed is constant and coupled to compressor, including 30 data series; and
3- Both turbines speed is variable, including 18 data series.

17 variable recorded by user in the experiments are: compressor inlet air pressure P_1, compressor inlet air temperature T_1, first turbine and compressor speed N_1, first turbine outlet hot air pressure P_4, first turbine outlet hot air temperature T_4, environment temperature T_a, environment pressure P_a, combustion chamber inlet air temperature T_2, combustion chamber hot air temperature T_3, dynamometer torque T_q, second turbine outlet hot air temperature T_5, fuel consumption $\dot{m}_f$, combustion chamber inlet air pressure P_2, combustion chamber hot air pressure P_3, second turbine and dynamometer speed N_2, second turbine outlet hot air pressure P_5, difference between inlet air and environment pressure dP_n.

2-3- Mathematical modeling of performance variables

Suppose that the apparatus compressor operates with a mass flow rate of $\dot{m}_a$ and changes the absolute pressure of air from P_1 to P_2, so the overall compression ratio shown by r_{CO} , is defined as follows:

$$r_{CO} = \frac{P_2}{P_1} \qquad (4)$$

During the process of air compression and its pressure change, the air temperature increases from T_1 to T_2. The input work needed to do this compression is theoretically calculated from following formula:

$$W_{CO} = \dot{m}_a C_{pa}(T_2 - T_1) \qquad (5)$$

C_{pa} is the specific heat capacity of air in constant pressure which is usually considered to be equivalent to 1.005 kJ/kgK. It should be noted that C_{pa} depends on air actual temperature.

Through comparison of theoretical value from formula (2-3) which is based on nonisentropic compression process, the efficiency value of compression process can be calculated. Ideal work value needed to change the temperature from T_1 to T_2 with the pressure ratio of r_{CO} may be shown as follows. Isentropic efficiency can be defined by following formula:

$$\eta_{COi} = \frac{W_{COi}}{W_{CO}} = \frac{T_{2i} - T_1}{T_2 - T_1}(\times 100\%) \quad (6)$$

where T_{2i} is an ideal value that is less than the actual value for the compressor.

The gas burnt in combustion chamber must have a homogenous temperature in the outlet. As a result, the efficiency can be calculated through comparison of measured actual temperature and the temperature which is theoretically computed for different percentages of air and fuel mixture.

$$\eta_{ch} = \frac{T_3 - T_2}{\Delta T_{ch}}(\times 100\%) \quad (7)$$

where ΔT_{ch} is the theoretically calculated temperature increase.

An acceptable solution to theoretically compute temperature increase is to use formula (8). The formula includes discreteness correction coefficients and other effective factors:

$$\Delta T_{ch} = \frac{u - 10T_2}{C_{pa} \cdot \frac{A}{F} + 6.6} + \delta \quad (8)$$

In this formula u is specific internal energy of fuel (for kerosene it is 43.76E6 J/kg), A/F mixing rate of air and fuel, δ correction coefficient which is considered 2 degrees centigrade and C_{pa} specific heat capacity of air at constant pressure which is usually equal to 1.005 kJ/kgK.

Using a method similar to what was used for the compressor, turbine expansion coefficient is calculated as follows:

$$r_{tu1} = \frac{P_3}{P_4} \quad (9)$$

But in an isentropic process, the relation between temperature changes and pressure ratio is determined according formula (10):

$$\frac{T_{4i}}{T_3} = \left(\frac{P_4}{P_3}\right)^{(\gamma - 1/\gamma)} = \left(\frac{1}{r_{tu}}\right)^{(\gamma - 1/\gamma)} \quad (10)$$

However, because of frictional heat generated in the turbine due to gas expansion, this ratio is more than one; but since the efficiency value must be less than 100%, the isentropic efficiency is calculated using the following formula:

$$\eta_{tui} = \frac{T_3 - T_4}{T_3 - T_{4i}}(\times 100\%) \quad (11)$$

and by inserting E. (10) into Eq. (11):

$$\eta_{tui} = \frac{T_3 - T_4}{T_3\left(1 - \left(\frac{1}{r_{tu}^{(\gamma - 1/\gamma)}}\right)\right)}(\times 100\%) \quad (12)$$

It should be noted as the gas temperature has been increased during the process, thus the specific heat coefficient of air would be variable. With an approximate calculation, its value may be considered as 1.33. The important point is that because the primary task of the turbine is to operate the compressor, so its output power must be equal to that of the compressor.

The power generated by free turbine is calculated through formula (13):

$$W_{tu2} = (\dot{m}_a + \dot{m}_f)C_{pg}(T_5 - T_4) \quad (13)$$

Overall efficiency of engine with regard to the output power is calculated through formula (14):

$$\eta_0 = \frac{\text{Measured power}}{\text{Input heat}} \quad (14)$$

and more clearly would be as follows:

$$\eta_0 = \frac{\text{Measured power}}{\dot{m}_f HV} \quad (15)$$

where *HV* is the heating value of fuel that is nearly equal to $\boldsymbol{u}$. Rewriting formula (15) would lead to formula (16) and eventually to the formula (17):

$$\eta_0 = \frac{\text{Measured power}}{\dot{m}_f C_{pa}(T_3 - T_2)\eta_{ch}} \quad (16)$$

$$\eta_0 = \frac{(\dot{m}_a + \dot{m}_f)C_{pg}(T_5 - T_4)}{\dot{m}_f C_{pa}(T_3 - T_2)\eta_{ch}} \quad (17)$$

Occasionally in some references, the above formula in changed as follows:

$$\eta_0 = \frac{(T_5 - T_4)}{(T_3 - T_2)\eta_{ch}}(\times 100\%) \quad (18)$$

In order to measure the amount of fuel consumed to generate one kilowatt power in terms of g/kwh, formula (19) can be used:

$$sfc = \frac{\text{Fuel consumption}}{\text{Power output}} = \frac{\dot{m}_f}{W_{tu2}} \quad (19)$$

If $\dot{m}_f$ is calculated in g/s and W_{tu2} in KW, then:

$$sfc = \frac{\dot{m}_f}{W_{tu2}} \times 3600(g/kWh) \quad (20)$$

2-4- Neural Network

Neural network is a massive set of parallel processors with intrinsic capability to store and utilize experimental information. This network resembles the brain at least from two aspects: (1) it has a stage called learning; (2) synaptic weights are used to store knowledge. The task of neural network is learning, something nearly similar to a child's learning. In common neural networks the learning is supervised. It is one of the modern methods of predicting a function using a set of inputs. Utilizing different neurons in many sublayers, the neural network tries to establish a mathematical model between input data and the required output. This method firstly divides the data into three parts: training, verification and testing data. In the next stage, by guessing mathematical model, neural network training is done and subsequently the model is verified and then tested.

In this section, in order to facilitate the obtaining of apparatus performance characteristics in different conditions, the neural network method is used to relate laboratory conditions and the data under study with the output so that the user will achieve the necessary results in less time.

One the most important stages of working with neural networks is the selection of correct data and their preparation. The training set should be selected randomly from among all the available samples. The number of training samples is a function of the number of network inputs and also depends on the quality of data and the complexity of the problem. The more the number of inputs, the more will be the training samples. One of the most important conditions of training set is that it should cover all the values of inputs range. Moreover, it would be better to cover all the possible values of outputs and also, the number of training samples to be the same for every output value.

In this research, 17 recorded variables were used as the input of the neural network. These 17 variables are those recorded by the user in the experiments. The apparatus heat efficiency which was influenced by all the mentioned variables was considered as the output of neural network. The division of these 78 data series was described in the earlier sections. Back propagation algorithm is usually used for the training of the network.

According to this algorithm, the training steps are:

a- Allocation of a random weight to each one of the connections;
b- Selection of the input and output vector proportional to that;
c- Calculation of neuron output in each layer and eventually the neurons output in output layer;
d- Updating the weights with the method of propagation of network error to the previous layers where the error occurs from the difference between actual output and the calculated output;
e- Evaluating the trained network performance using some defined indexes like error mean squares and finally returning to the step ‘c’ or the training end.

The best topology of neural network is determined using two criteria of determination coefficient and error least mean squares. The best topology has the highest determination coefficient and the lowest error mean squares. Eqs. (21) and (22) show how to calculate determination coefficient and error mean squares.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(a_i - p_i)^2 \qquad (21)$$

$$R^2 = 1 - \left[\frac{\sum_{i=1}^{n}(a_i - p_i)^2}{\sum_{i=1}^{n}(\bar{a}_i - p_i)^2}\right]^{\frac{1}{2}} \qquad (22)$$

where a_i is 'i'th actual data obtained from the computations, p_i 'i' th predicted data by network and N number of observations.

As was explained earlier, 70% of laboratory data available in various stages of this research were used as training data, 15% as verification data and the other 15% as testing data.

3- Results and Discussion

3-1- Performance Variables Calculation

Since the air is the operating fluid in this apparatus and depending on the environment, there are differences in its characteristics, so the obtained data must be modified using the necessary correction coefficients. After modification of the data values, performance variables of turbine parts will be computed using the formula presented in section 2-2. Subsequently, in order to investigate the results, the functional graphs of system parts have been shown. At first, the graph of compressor efficiency changes is shown in Fig. 2 and then the graph of first turbine efficiency changes in Fig. 3.

As is shown in Figs. 2 and 3, when the free turbine work to heat ratio increases, the compressor efficiency approximately increases; while the first turbine efficiency has a maximum and before and after that the turbine efficiency decreases.

In Fig. 4, the graph of thermodynamic cycle heat efficiency changes of gas turbine in terms of free turbine work to heat ratio which indicates the overall performance of the apparatus, has been shown.

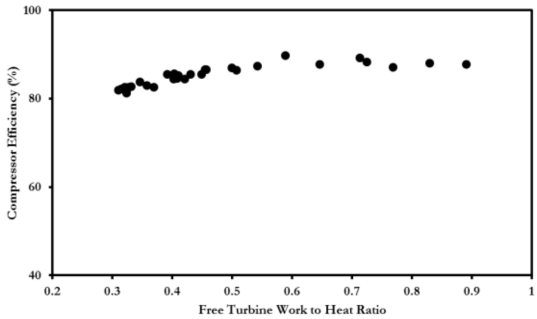

Fig. 2 The compressor efficiency changes in terms of free turbine work to heat ratio.

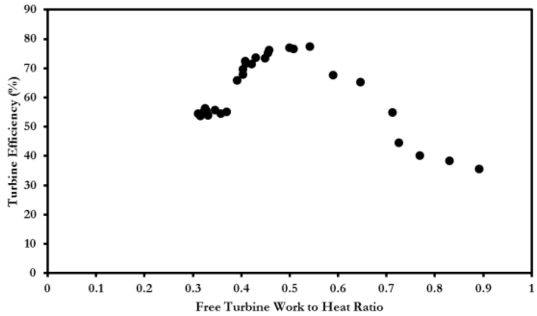

Fig. 3 The first turbine efficiency changes in terms of free turbine work to heat ratio.

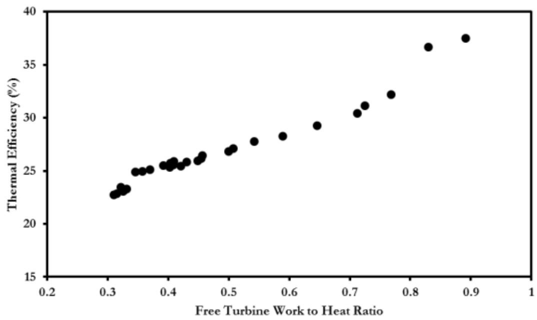

Fig. 4 Heat efficiency changes in terms of free turbine work to heat ratio

As shown, the heat efficiency increases with the increase in free turbine work to heat ratio value.

3-2- Neural Network Results

In the beginning, the graph of error histogram for neural network is depicted in Fig. 5.

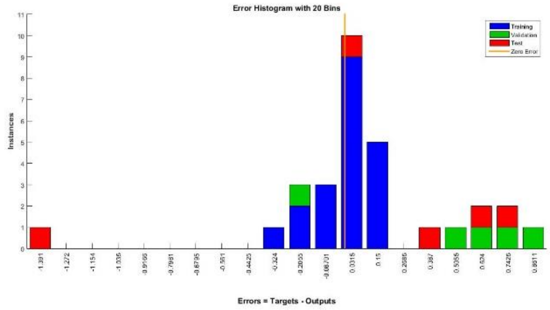

Fig. 5 Error histogram of training, verification and testing stages of neural network

As shown in the figure, error distribution values for training, verification and testing data are scattered around the base line which is the zero value. This indicates the quality of neural network. In this network, highest errors absolute values of training, verification and testing data were 0.32, 0.86 and 1.39 respectively.

4- Validation

In Fig. 6, the accuracy of transfer function which has been used to connect input and output layers is depicted. In this figure, the graph of neural network output data in terms of their target values for training, verification, testing and overall data is shown. Good accuracy of these graphs indicates the acceptable accuracy of neural network. As is seen in the figure, the overall error least mean square is equal to 0.9935 which indicates the good accuracy of the designed neural network. In the stages of verification and testing, the errors least mean squares were 0.997 and 0.989 respectively. Determination coefficient in training stage was equal to $6.82 \times 10^{-4}$and the error least mean squares was 9.992×10^{-1}.

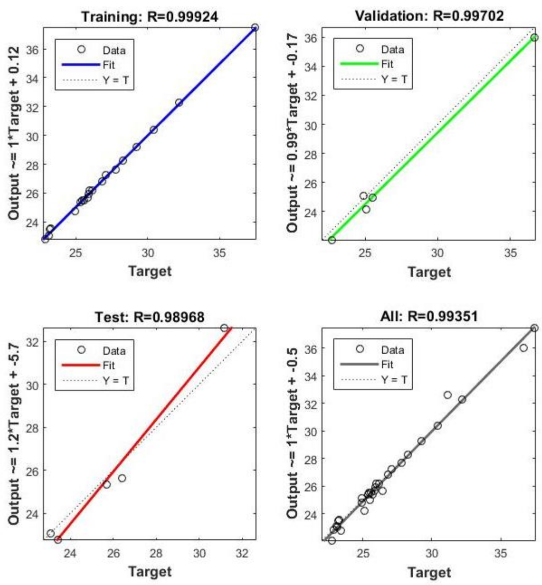

Fig. 6 Correlation coefficient value for training, verification, testing and overall stages of neural network

5- Conclusion

This research aimed at analyzing laboratory data of two-shaft radial gas turbine model GT-185 manufactured by Tecquipment company using artificial neural network. At first, the needed data were recorded in laboratory under different operating conditions. Then the data values were modified. This modification included unification of data units and the modification of their value in terms of standard input conditions so that comparison could be possible among data recorded in different days. In the next stage, performance variables of compressor, heat turbine and free turbine were calculated using presented formulas. Finally, in order to create a connection among recorded data and the heat efficiency of the apparatus, a neural network was designed using neural network toolbox of Matlab software and its quality was investigated. From laboratory data of this research in different cases, 70% were used as training data, 15% as verification data and the other 15% as testing data. Studying the error histogram of designed neural network showed that the error value of transfer function which was used to create relation between input and output was less than 0.1%. Investigating the accuracy showed that good accuracy of output data graph of neural network in terms of their target values for training, verification, testing and overall data indicated good accuracy of neural network. Drawing the graph of heat efficiency changes in terms of free turbine work to heat ratio showed the increasing free turbine work to heat ratio resulted in an increase of heat efficiency.

Table of Symbols and Signs

$\dot{m}$	Mass flow rate
N	Revolving speed
p	Pressure
r	Compression Ratio
T	Temperature
T_q	Torque
u	Fuel Specific Internal Energy
W	Power
γ	Specific Temperature Ratio
δ	Temperature Correction Coefficient
η	Efficiency

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