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Forecasting of the thermal lag type of Solar Stirling Engine output power performance, using Neural Networks

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Abstract: *In this article the simulation and forecasting of solar sterling engine performance has been done, using the Artificial Neural Networks (ANN). The analytical data of measured previous references have been utilized for training the neural network. Input parameters contain the angular velocity, temperature, heat resistance, course length, piston diameter, tank volume, heat buffer, gas tank volume and the output parameter is the maximum output power. Utilized training algorithm has been the Levenberg-Marquardt algorithm that is a kind of Recurrent/Feedback networks. Multi neural networks with various neurons have been utilized in hidden layer for simulation and then the best network has been chosen for prediction, surveying their performance. Applied performance evaluation method was the Mean Square Error (MSE) and regression analysis. Using this method, the system performance can be assessed in different situations in a very short time, without needing to solve the complex govern equations.*
Keywords: *Solar Thermal lag Sterling Engine, Artificial Neural Networks, Output power performance forecasting.*

I. Introduction

Nowadays the energy plays a crucial role in improving and development of human societies. Running out the fossil fuels, their pollution properties and environmental problems caused the researcher’s attention to the other kind of reproducible energies such as solar energy. The broadest source of energy in the universe is the solar energy.The amount of energy, comes from the sun during an hour, is more than whole energy, consumed by the Earth residents during a year. Among the other countries, Iran has a high rank in energy receiving from the sun. The amount of solar radiation in Iran is about the 1800 to 2200 kwh/m2 during a year that is more than the world average. The Stirling engine is a kind of ideas, has attracted the attention of interested during the recent years. Low pollution, low sound and vibration noise, low fuel consumption, using of multiphase fuels (solid, liquid, gas, animal fuels and solar energy as the best of them) and recently the consumption of nuclear fuel are the advantages, determines the good business prospects in research about the stirling engines. In the past, the huge attempt has been done in modelling and simulation of α, β, γ and thermal lag of solar stirling engines. In performed studies the numerical and analytical methods have been used for simulation but the Artificial Neural Networks have not been utilized in solar stirling engine simulation so far. Therefore the Artificial Neural Networks will be used in this research for the simulation of stirling engine output power performance.Cheng and Yang in 2012 have simulated numerically the thermodynamic behavior of stirling engine thermal lag upon to the improved model theory. The geometric effects and parameters such as heating and cooling of temperature, the volume of tank, thermal resistance, course length and the amount of cylinder inner diameter have been surveyed in output power and thermal efficiency (Cheng and Yang, 2012). Altamirano et al. in 2013 presented two model of control volume for thermal lag engine (Altamirano et al, 2013). Using the artificial neural networks for the thermal lag type of solar Stirling engine output power performance forecasting is the differences of this article comparing to the other studies.

The Artificial Neural Networks and Their Applications

Artificial Neural Networks are one of the important branches of Artificial Intelligence that consist of related nonlinear parts, called Neuron. Unlike the previous simulation models, the neural networks are made by the lab or analytic data and work in black box procedure that means there is no information about their performance (Xie et al, 2009).After the neural network training, an especial input gives an especial output. Generally the lots of these pairs are used to train the neural network that called supervised training (Kia, 1387).Generally the network consist of an input, hidden and an output layer. The information is saved in connected weights and the network training is the changing of connected weights, using the new data. Figure 1 and 2 show the performance of a simple neuron in neural network and the performance of a multilayer neural network respectively (Kalogirou, 2001).

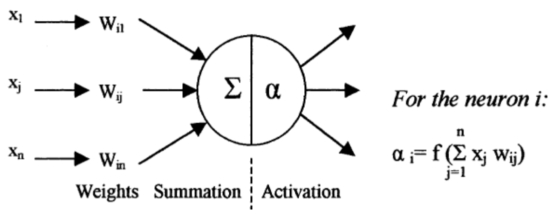

Fig1: the performance way in a neuron of neural network.

A neural network can forecast the similar problems after the training (Kalogirou, 2001).

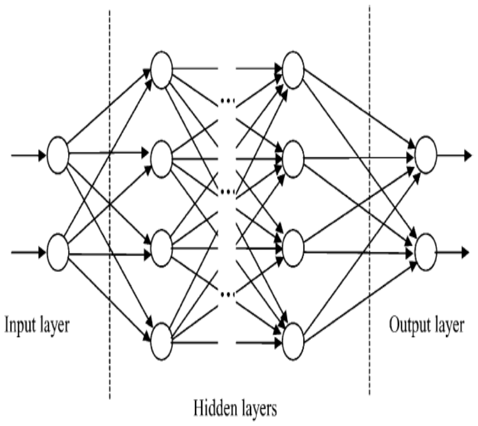

Fig2. Schematic diagram of a multilayer neural network.

Assessment of simulation performance by the neural network is done via the reggression analysis of experimental data and network outputs. The creteria that are used in network performance determination are as below (Xie et al, 2009):

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{N} (a_i - p_i)^2}{\sum_{i=1}^{N} a_i^2} \right) \quad (1)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (a_i - p_i)^2} \quad (2)$$

$$COV = \frac{RMSE}{\sum_{i=1}^{N} a_i} \times 100 \quad (3)$$

Where the N is the number of data and a and p are the real and forecasted data respectively. The lesser COV and RMSE in addition to R^2 closer to 1 show the better performance of network.

Parameter selection and Neural Network construction

The input parameters are angular velocity, temperature, thermal resistance, course length, piston diameter, the volume of thermal buffer tank, the volume of gas tank. The output parameter is the maximum output power. The constructed schematic of network is shown in figure 3.

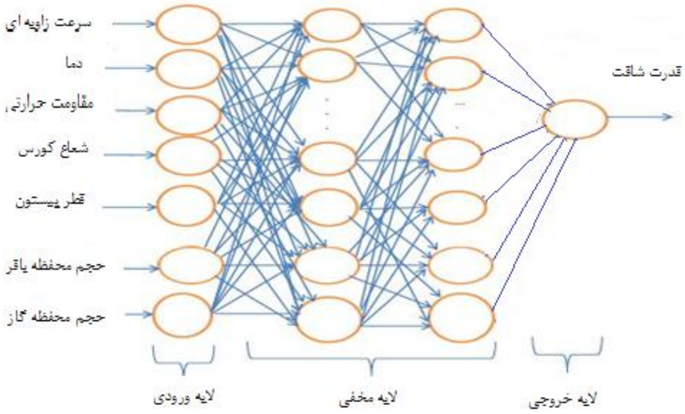

Fig3. The neural network schematic for performance prediction.

The number of neurons in hidden layer has been assessed in various situation and the best forecasting situation has been utilized for the prediction of solar stirling engine performance. The analytic data of previous references have been used in network training.

Validation

In figure 4 the temperature of gas in simulated situation by the neural networks was compared by the gas temperature in analytic data.The amount of error in 800, 1000 and 1200 K° are 4, 1.5 and 2.5 % respectively. Also in figure 5 the volume of simulated gas tank was compared by the volume of gas tank for analytic data. The error amount of gas tank volume equal to 30, 10 and 5 cm3 is 2.24, 3 and 4 % respectively.

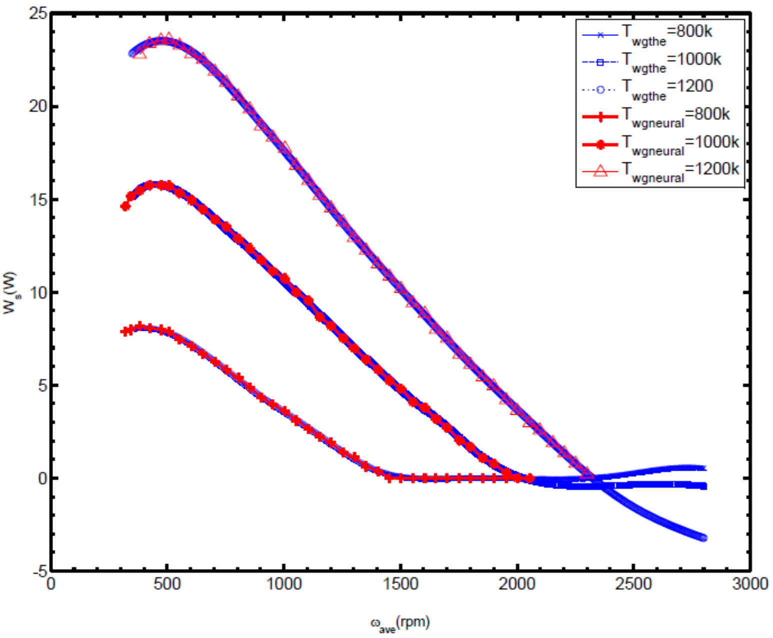

Fig4. The comparison of predicted gas temperature by the neural network to gas temperature of analytic data.

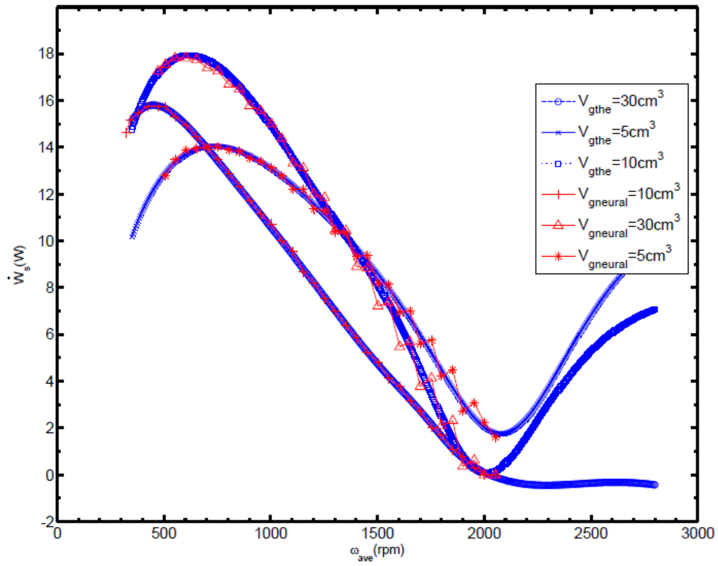

Fig5. The comparison of predicted gas tank volume by the neural network to the gas tank volume of analytic data

II. Results

The best trained neural network structure has been shown in figure 6, considering the least RMSE and the maximum R2.

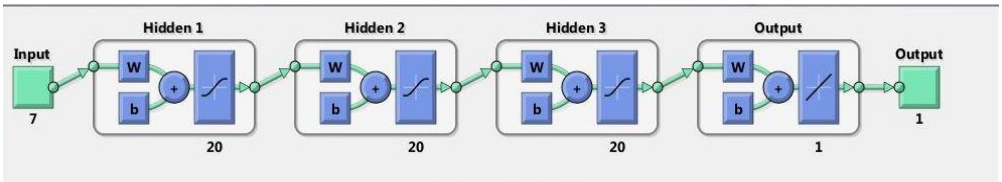

Fig6. The designed neural network structure.

The neural network toolbox of Matlab software has been used for network training. The 572 data were used for this purpose. Figure 7 shows the regression analysis for training, validation and test of networks. In figure 8 the changes of RMSE during the training process has been shown and also the figure 9 reveals the error gradient changes, μ and validation error.

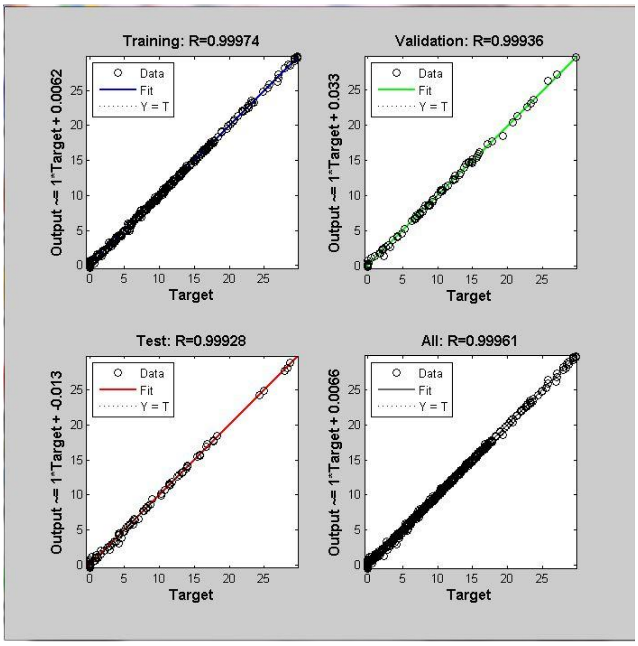

Fig7. Regression analysis for training, validation and test of data network.

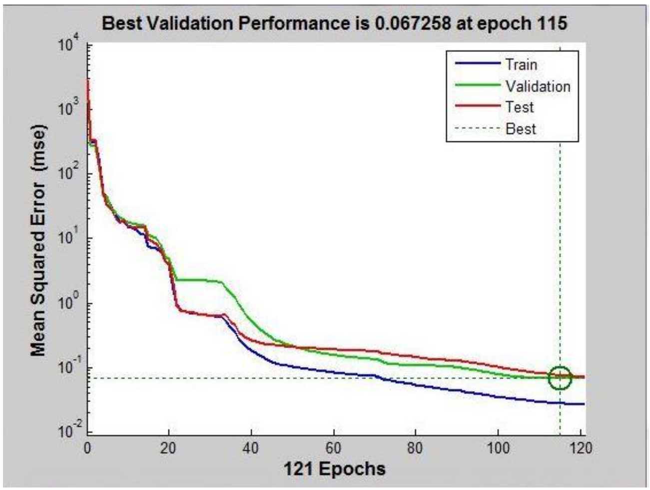

Fig8. The RMSE changes during the training process.

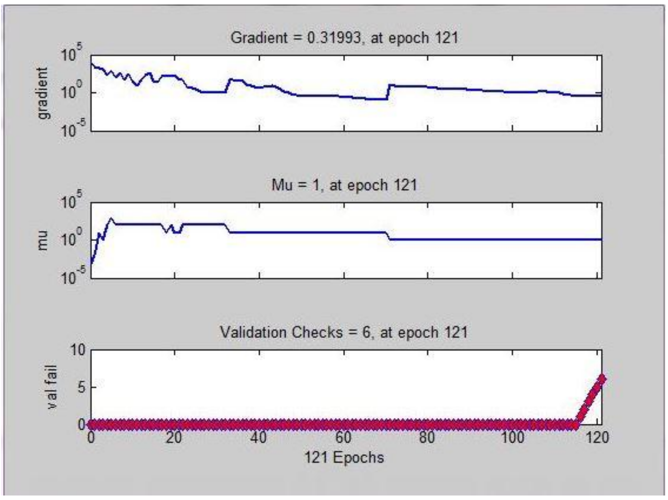

Fig9. The variation of error gradient, μ and the validation error.

In figure 10 the thermal resistance of 1, 0.5 and 0.75 K°/watt has been shown. Using the neural network the amount of output power in various angular velocities was obtained at 0.75 thermal resistance.Figure 11 shows the predicted gas tank volumeby the neural network. The output power in different angular velocities in 20 cm3 was obtained by the neural network.

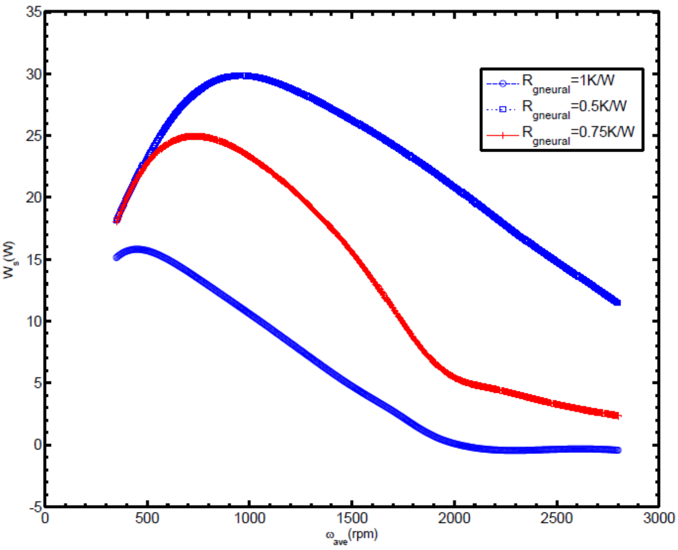

Fig10. Changes of predicted thermal resistance by the neural network

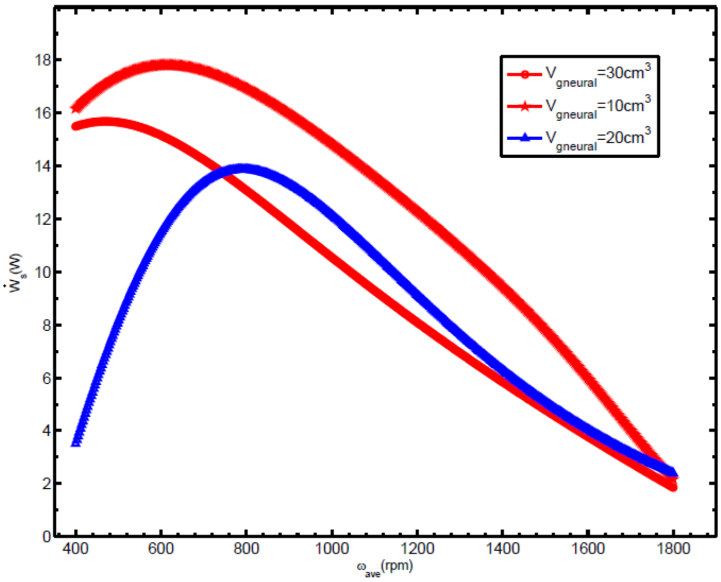

Fig 11. Changes of predicted gas tank volume by the neural network.

III. Conclusion

In present research, an artificial neural network was applied successfully for simulation of performance of solar thermal lag Stirling engine shaft power. The sigmoidal functions were used for the network unit's connection. The network was trained by the experimental data. The input parameters were the angular velocity, temperature, thermal resistance, course length, piston diameter, the volume of thermal buffer tank, the volume of gas tank. The results were assessed by the correlation coefficient, RMSE and COV coefficients that showed the high accuracy in prediction process of stirling engine, using the limited experimental data. The overall result of this research shows that, using of this method is suitable in engine performance prediction and this method can be used instead of time consuming and high cost experimental works and also the complex numerical calculations for the study of solar thermal lag Stirling engine performance.

List of Symbols

The number of data	N
Correlation Coefficient	R^2
Coefficient of variation	COV
Mean Square Error	RMSE
Temperature	T

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