**International Conference on Applied Energy 2019**
**Aug 12-15, 2019, Västerås, Sweden**
**Paper ID: 0786**

# PREDICTION OF THE PERFORMANCE FOR ALPHA-TYPE STIRLING ENGINE THROUGH ARTIFICIAL NEURAL NETWORK TECHNIQUE

Han Jiang[1], Anas A. Rahman[1, 2], Xiaoqing Zhang[1*]

1 Department of Refrigeration and Cryogenics, Huazhong University of Science and Technology (HUST), Wuhan, China

2 Department of Mechanical Engineering, Future University in Egypt (FUE), Cairo, Egypt

**ABSTRACT**

This study involves the application of artificial neural network (ANN) as an intelligent approach to predict the output power of one alpha-type Stirling engine under some operating conditions. One ANN model had been developed based on experimental data from published literature. Output power as one of the performance indicators, was chosen as a response to input parameters, heat source temperature, engine speed and charging pressure. A multi-layer feed-forward network with a back-propagation algorithm had been proposed for such a prediction. The ANN model had been proven to be desirable in accuracy for predicting the output power by comparing the model results with experimental ones under the same operating conditions. This work would provide an effective approach based on ANN technique for solving complex design problems either with linear or nonlinear nature.

**Keywords:** Stirling engine, Artificial neural network, Output power, Heat source temperature, Engine speed, Charging pressure

**NONMENCLATURE**

| | |
|---|---|
| *Abbreviations* | |
| ANN | Artificial Neural Network |
| *Symbols* | |
| *t* | target (Actual output) |
| *o* | Network output (Predicted output) |

## 1. INTRODUCTION

Stirling engine has attracted increasing attention in recent decades for its unique advantages including using environmentally-friendly working substances, high efficiency, the ability to utilize low grade energy and quiet operation [1]. Stirling engines can be classified according to pistons arrangement into alpha, beta and gamma type [2] and each type can be applied in different occasions.

The performance indices for a Stirling engine including output power, shaft torque and efficiency depend primarily on the system parameters with respect to mechanical connections, operating conditions, structure geometry and materials properties [1]. The identification of the relationship among those design parameters and desired performances is considered the basis for appropriate design of Stirling engines. However, the performance of Stirling engine is still difficult to obtain greatly due to the performance can be influenced by numerous factors and the influencing process is so complex and usually nonlinear. In past few decades, many researches were focused on analysing, designing and testing of Stirling engines [2]. Analytical solutions to obtain the performances are usually not accurate enough for nonlinear problems with too many assumptions. The experiments works can provide more accurate results, but the information obtained from experiments is limited, mainly because the experiments are costly, time consuming and inflexible. Therefore, a method which could help to produce more information only based on limited experiment data is required.

Recently, ANN as a purely data driven model, has become a popular technology in many thermal science and engineering fields [3, 4]. The ability of ANN to learn from examples makes it efficient problem-solving paradigms in recognizing and learning underlying implicit relations between inputs and outputs regardless system dimensionality or nonlinearity besides the high tolerance to data containing noise and measurement errors. On the other hand, ANN has been considered an effective alternative to traditional statistical techniques for function approximation and data fitting without hypothetical data distribution premise. These advantageous features could possibly make ANN more attractive alternatives to statistical approaches and numerical models.

Various degrees of research work were implemented using ANN [4] or ANN hybridized with other optimization methods [5] in order to predict the performances of Stirling engines under different design conditions. Undoubtedly, these researches demonstrated that ANN models are capable of mapping the implicit relationship between considered operating parameters and the corresponding responses. In this regard, it was noticed that most of research works were focused on beta-type or gamma-type Stirling engines due to their high output power density. However, it is noteworthy that alpha-type Stirling engine has many significant advantages over other types including (i) Simple mechanism, (ii) Heating and cooling occur in separate cylinders which enables the engine to be used in applications with a large enough external heat transfer surface, (iii) Possibility to operate in either single-acting or interconnected double-acting piston configurations. Çinar [6] did an experiment for alpha-type Stirling engine to investigate the relationship between output power and some operational conditions. In the present study, ANN is introduced to map the implicit relationship between some operating parameters and corresponding performances based on the experiment results from Çinar [6].

## 2. ARTIFICIAL NEURAL NETWORK MODEL FOR PREDICTING THE OUTPUT POWER

### 2.1 Physical Model

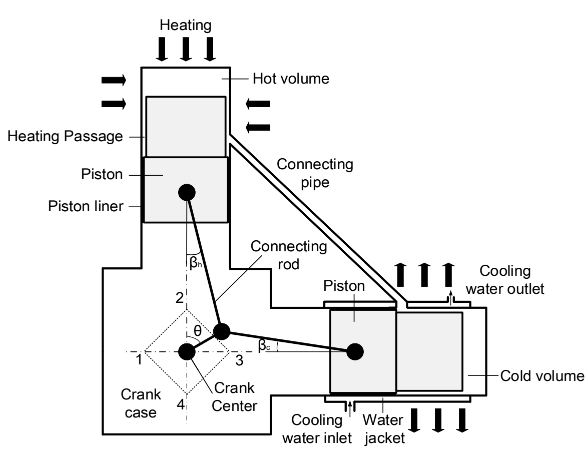


Fig 1 Schematic diagram of alpha-type Stirling engine

As shown in Fig. 1, the alpha-type engine used in [6] consists of two power pistons in separated cylinders, a crankcase, a crankshaft, two connecting rods, a flywheel and a connecting pipe inside which the regenerator is situated. More construction details are given by Çinar [6].

### 2.2 Determination of data samples

For the sake of convenience of comparison, 62 experimental data from [6] would be used as the data samples to build the ANN model. Heat source temperature, engine speed and charging pressure were considered as the input parameters influencing the output power. Practically, it was verified that the output power is closely related with but roughly proportional to those three parameters [6, 7]. Here, the data sample values of heat source temperature range from 800℃ to 1000℃ while the values of engine speed range from 176 r/min to 471 r/min and the charging pressure values range from 1 bar to 3 bar. These three parameters have a significant influence on the output power of the engine.

For the ANN model, the considered 62 data samples were divided into two groups. The first group includes 54 data samples for the purpose of building the model while the second group including the remaining 8 data samples was used as unseen data samples for the purpose of verifying the prediction ability. The first group data samples were split into three data sets: 70% for training to learn, 15% for validation to minimize over-fitting and 15% for testing to assess the generalization performance of trained model. These three data sets were normalized, then randomized and finally introduced sequentially to the ANN model.

### 2.3 Optimization of ANN model

Optimization of ANN aims at minimization of its objective function (i.e., error function) during training process through tuning the values of weights and biases of the network. ANN models are often characterized by structure, neuron characteristics, learning parameters, training algorithm and training function, which represent the constraints for optimizing the network performance. Structurally, a typical feed-forward neural network with one hidden layer as shown in Fig. 2(a) is commonly adopted in majority of applications. Herein, the mean square error (*MSE*) is commonly used as the objective function for feed-forward neural networks which gives the average squared error between network outputs and targets during the validation phase as given in Eq. (1).

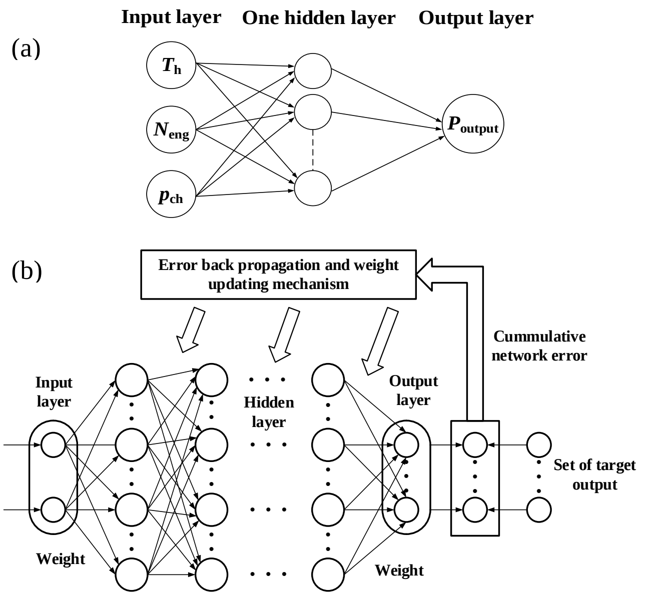


Fig 2 (a) A three-layer ANN model for the alpha-type Stirling engine; (b) A multi-layer feed-forward ANN with a back-propagation algorithm

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - o_i)^2 \qquad (1)$$

Besides, the number of input and output neurons is determined according to the considered modelling problem while number of hidden neurons needs to be accurately optimized. In this regard, the number of hidden neurons was changed iteratively from 2 to 20 with a gradual step of 2. Moreover, back-propagation algorithm as shown in Fig. 2(b) with Levenberg-Marquardt training function, was adopted here for low- and moderate-sized networks. On the other hand, three criteria were set in order to evaluate the network performance. The first criterion is to choose the least MSE during the validation phase. The second criterion is to decrease the complexity and network size if possible. Finally, the third criterion is to analyze the regression between the network responses and corresponding targets (actual outputs) from the correlation coefficient ($R^2$) as illustrated in Eq. (2). In general, $R^2$ value varies between 0 and +1, where $R^2$ value close to +1 indicate a robust positive linear correlation between the network outputs and targets, while the values near to 0 indicate a very weak correlation.

$$R^2 = 1 - \left( \frac{\sum_i^n (o_i - t_i)^2}{\sum_i^n (t_i)^2} \right). \qquad (2)$$

The proposed ANN model had been trained several times until the error between predicted and actual values of output power was minimized. It can be noticed from Fig. 3(a) that *MSE* was minimized at 10 hidden neurons with a value of 0.0036. In addition, the performance of the proposed ANN in predicting the output power was validated through analyzing the correlation coefficient ($R^2$) between predicted and actual values during testing phase as shown in Fig. 3(b), from which the highest $R^2$ value of 0.98 was achieved.

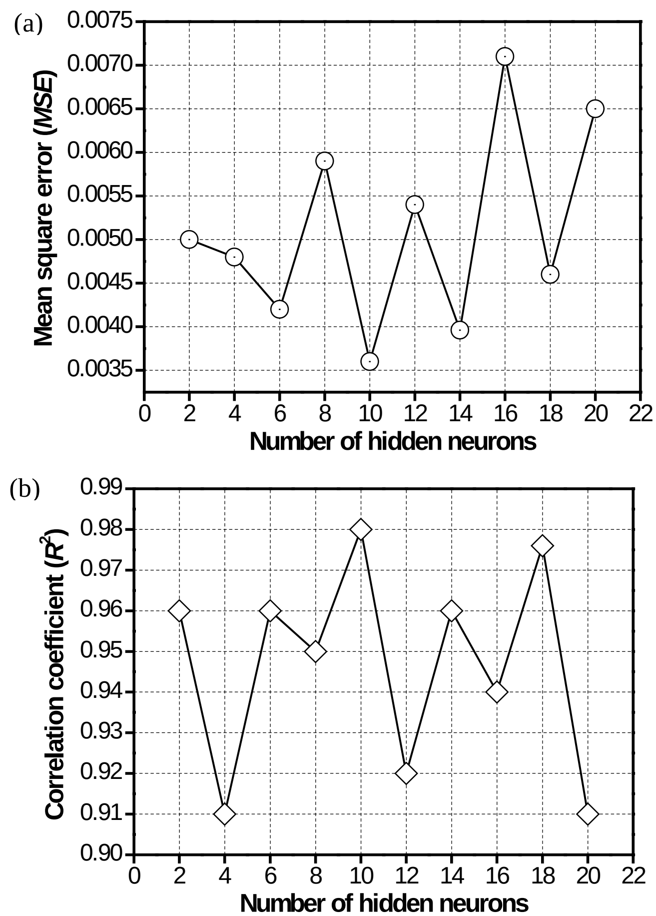


Fig 3 (a) Sensitivity of the *MSE* for the network model *vs.* number of hidden neurons; (b) Variation of correlation coefficient ($R^2$) between network and actual outputs *vs.* number of hidden neurons

In more detail, the regression plots were presented in Fig. 4. From this figure, there is a very good fit between predicted outputs and targets (actual outputs) due to higher values of regression ($R^2$) during training, validation and testing phases. These regression plots verify that established ANN model with the configuration of 3-10-1 can accurately predict the output power of alpha-type Stirling engine within the covered range of study.

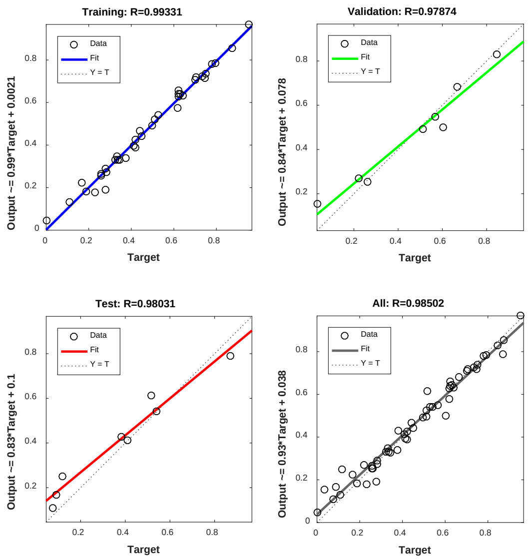


Fig 4 Regression plots for training, testing and validation phases

## 3. RESULTS AND DISCUSSIONS

In order to verify the prediction ability of ANN model, the 8 data samples of the second group mentioned previously, which were not still used in building the model, had been introduced to our established network (3-10-1). The predicted results from the established ANN model were compared with corresponding experimental results under same operating conditions as shown in Table 1. It can be noticed that the predicted results from ANN model were in a very good agreement with the experimental results with the average prediction error percentage of 1.53%. This implies the strong ability of established ANN model to predict the output power of the considered alpha-type Stirling engine with a good degree of accuracy for any input values within the covered range of this study.

Table 1. Comparison of predicted results by ANN model with experimental results (Note: data samples were extracted from Ref. [6])

| $p_{ch}$ [bar] | $T_H$ [°C] | $N_{eng}$ [r/min] | $P_{exp}$ [W] | $P_{pred}$ [W] | Error [%] | Average prediction error [%] |
|---|---|---|---|---|---|---|
| 2 | 850 | 286 | 8.46 | 8.56 | 1.15 | |
| 2 | 1000 | 286 | 13.82 | 13.75 | 0.49 | |
| 3 | 1000 | 214 | 15.36 | 15.39 | 0.17 | |
| 3 | 1000 | 286 | 18.16 | 18.87 | 3.92 | 1.53 |
| 3 | 1000 | 413 | 15.40 | 15.58 | 1.22 | |
| 2 | 950 | 286 | 12.38 | 12.19 | 1.50 | |
| 3 | 950 | 286 | 15.96 | 15.88 | 0.53 | |
| 1 | 950 | 286 | 5.30 | 5.12 | 3.27 | |

## 4. CONCLUSIONS

One artificial neural network model had been developed for alpha-type Stirling engine to predict the output power under specific operating conditions. It was found that one hidden layer with optimal 10 neurons can provide a better prediction performance. The average percentage error of predicted output power values compared to experimental ones was found to be 1.53 % which indicates high accuracy of our model and proves that well-trained neural network models can provide fast, accurate and consistent results. Moreover, according to our research, ANN is able to be considered a supplement for experiments to produce more related information related with Stirling engine. Further applied research will be devoted to modelling of complex design problems including complex mappings, parameters identification, as well as the optimization for Stirling engines and their key components.

## ACKNOWLEDGEMENT

This work was supported by the National Natural Science Foundation of China (NSFC) (Grant No. 51476062).

## REFERENCE

[1] Walker G. Stirling engines. 2th ed. Clarendon: Oxford; 1980.

[2] Hachem H, Gheith R, Aloui F, Nasrallah SB. Technological challenges and optimization efforts of the Stirling machine: a review. Energy Convers. Manage. (2018), 171:1365-87.

[3] A. Rahman A, Zhang X. Prediction of Cooling Load for a Standing Wave Thermoacoustic Refrigerator through Artificial Neural Network Technique. Energy Procedia. (2017), 142:3780-3786.

[4] özgören Y Ö, çetinkaya S, Sarıdemir S, et al. Predictive modeling of performance of a helium charged Stirling engine using an artificial neural network. Energy Convers. Manage. (2013), 67: 357-368.

[5] Ahmadi M H, Sorouri Ghare Aghaj S, Nazeri A. Prediction of power in solar stirling heat engine by using neural network based on hybrid genetic algorithm and particle swarm optimization. Neural Comput & Applic. (2013), 22(6): 1141-1150.

[6] Çinar C, Aksoy F, Solmaz H, Yılmaz E, Uyumaz A. Manufacturing and testing of an α-type Stirling engine. Appl. Therm. Eng. (2018), 130:1373-1379.

[7] Batmaz I, Üstün S. Design and manufacturing of a V type Stirling engine with double heaters, Appl. Energy. (2008), 85:1041–1049.