Evaluation of the Stirling heat engine performance prediction using ANN-PSO and ANFIS models

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Abstract - The work presents the prediction performance results of three algorithms, namely Artificial Neural Network (ANN), Artificial Neural Network trained with Particle Swarm Optimization (PSO) and Adaptive Neuro-Fuzzy Inference System (ANFIS) models. ANFIS and ANN trained by PSO are applied to predict the power and torque values of a Stirling heat engine with a level controlled displacer driving mechanism. Data from experimental work done by Karabulut et al. is used to train and assess the algorithms. MATLAB is used to develop, implement and train the algorithms. The Root Mean Square Error (RMSE, Coefficient of determination (R2) and computational time are used to assess the performance of the algorithms.

Keywords- Stirling Engine, artificial neural network (ANN), particle swarm optimisation (PSO), adaptive neurofuzzy inference system (ANFIS)

I. INTRODUCTION

A concerning amount of environmentally related issues have surfaced due the world's energy consumption significantly increasing. This is mainly due to a widespread dependency on fossil fuels. In the past years, a great deal of attention has been drawn to the development of renewable energy. Stirling engines are amongst the technologies that researchers have developed to counter the use of technologies that have harsh environmental and social implications. A Stirling engine is a regenerative, externally heated engine operating with a cycle that has the same thermal efficiency as the Carnot cycle if it is ideal and without losses [1]. The engines have shown very distinct advantages including the ability to use air, hydrogen, nitrogen and even vapours [1] as the working fluid which have minimal toxic emission. The engine can be powered by an assortment of heat sources and is also capable of utilize solar radiation and waste heat as energy source [2]. The arrangement of a general Stirling engines is shown in Figure 1. The basic parts of a Stirling engine include: a work piston, a displacer piston, the crank, the flywheel, a heat source, a heat exchanger, and a heat sink. The work piston creates mechanical power via gas pressure. The displacer piston is applied to push gas between hot and cold working areas [3]. Many types of Stirling engines have been developed; however, none of the engines have become competitive enough to replace the commercial usage of internal combustion engines. Leakage of the working fluid out of the engine, larger volume and mass compared to internal combustion engines, longer response period to speed and power changing requirement, higher quality temperature resisting material requirements are some of the disadvantages associated with the Stirling engine [1]. The Stirling engine also presents reasonable efficiency which can be closer to the Carnot theoretical efficiency compared with other thermal engines. Due to the extensive losses experienced in the device, practically the devices rarely reach the required efficiency.

Considering the various parameters affecting the performance the performance of the Stirling engine; an improved adaptive neuro-fuzzy inference system, an artificial neural network model and artificial neural network trained by particle swarm optimization are proposed to estimate the power and torque. The main contributions of the paper are firstly to investigate the accuracy of the proposed Artificial Intelligence (AI) prediction techniques put forth and secondly to propose an alternative method to accurately predicting the power and the torque for a Stirling engine.

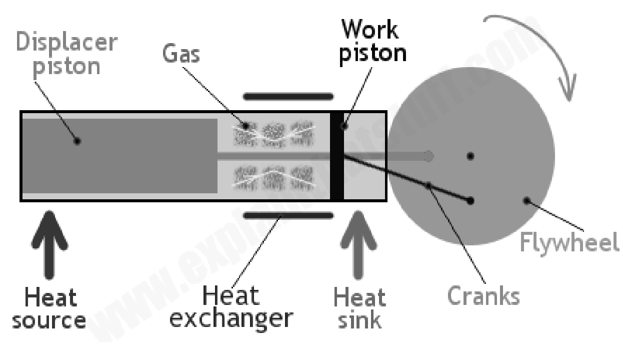


Figure 1: Schematic diagram showing the arrangement of a typical Stirling engine [3]

A. Artificial neural network

Artificial neural network is a type of artificial intelligence technique that mimics the behaviour of human brains [4]. ANN models are known for their ability to predict the relationship between the input and output variables of nonlinear, complex systems without requiring explicit mathematical representations [4]. Although various arrangements of ANN structures exist, a basic structure usually consists of three parts: an input layer, hidden layers and an output layer. Neurons in one layer are connected to all the neurons of previous and subsequent layers. Each connection between two neurons is allied with an adjustable synaptic weight. Using a suitable learning method, the network is trained to perform a particular function by adjusting the weights and biases. The training process continues until the error between the network output and the desired target falls below a predetermined tolerance or the maximum number of iterations (epochs) is reached [4]. For this work, the prediction accuracy of an ANN model and an ANN model trained with Particle Swarm Optimization is assessed. Figure 2 shows the arrangement of a typical ANN model.

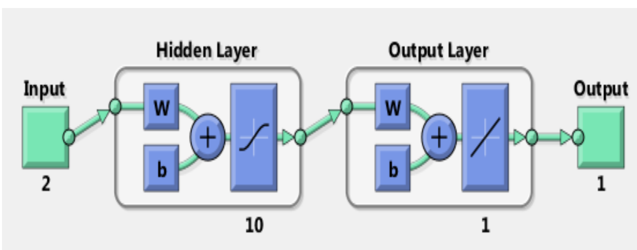


Figure 2: Schematic diagram showing a typical ANN architecture

The ANN-PSO algorithm has been implemented within MATLAB. The codes used are extracted from the unpublished paper developed by Alam [5]. The paper provides ANN model codes trained by Particle Swarm Optimization (PSO). The codes are customized to adapt to problems having any number of inputs/outputs parameters.

B. Adaptive Neuro-Fuzzy Inference System

The fundamental ideas behind the neuro-adaptive learning techniques have been described as simple. The technique applied in the model provide a method for the fuzzy modelling procedure to be trained using a data set, and to calculate membership function parameters that will best suit the associated fuzzy inference system (FIS) for given input/output set [6]. An adaptive neuro-fuzzy inference system (ANFIS) is a class of mixed adaptive networks in which artificial neural networks and fuzzy inference system are computed cooperatively. ANFIS makes use of the Takagi–Sugeno inference process in which the fuzzy regulations that map a nonlinear mapping between input space and the output space are generated using a number of fuzzy IF–THEN rules [4]. The ANFIS learning method works similarly to artificial neural networks. The MATLAB Fuzzy Logic Toolbox is utilized to develop an ANFIS model and to predict the power and torque of a Stirling engine. The structure of the ANFIS model developed is shown in Figure 3. The model comprises of five layers. The networks structure of the input-output membership function represents the engine speed and the pressure as inputs while using the power/torque as the output of the network

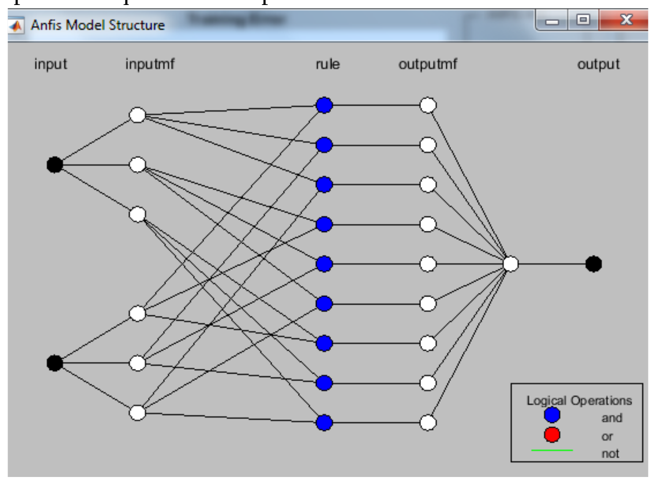


Figure 3: Schematic ANFIS structure developed within MATLAB

II. LITERATURE REVIEW

Although artificial intelligence techniques have a history dating back six decades ago, engineers have only established solid application of the technology in the past 20 years [5]. Artificial intelligence techniques have the ability to mimic the behaviour of the human brain and are famous for their ability to use a generalized technique instead of memorization. In recent years, artificial intelligence has been successfully applied for the modelling of different engines. Alborzi et al. [7] studied an artificial neural network which was applied successfully to simulate the performance of a solar thermal lag Stirling engine shaft power. The network was trained by using experimental data. The sigmoidal functions were used for the network unit's connection. The input parameters were the course length, piston diameter, angular velocity, temperature, the volume of thermal buffer tank, thermal resistance and the volume of the gas tank. The results were assessed by the correlation coefficient, RMSE and COV coefficients that revealed the high accuracy in prediction process of the Stirling engine, using limited experimental data. Jahirul et al. [8] assessed an ANN model to approximate Compressed Natural Gas (CNG) engine performance parameters including the brake-specific fuel consumption (bsfc), engine brake power (bp), and engine efficiency (η). According to their results, the R^2 values for the engine torque, brake-specific fuel consumption, and engine efficiency were found to be 0.978, 0.963, and 0.970, respectively, indicating that the prediction accuracy of the model was excellent. Ahmadi et al. [6] used neural network based on hybrid genetic algorithm and particle swarm optimisation (PSO) for the prediction of power and efficiency in a solar Stirling heat engine. The researchers used data consisting of 300 samples for training and 100 data samples for testing. The ANN model was set up based on a back propagation algorithm for the engine. The R^2 values for power and efficiency in the solar Stirling heat engine were 0.99959 and 0.9861, respectively. Deh Kiani et al. [9] studied ANN modelling of a spark ignition engine to estimate the engine thermal balance. The obtained results indicate that the ANN yield has great accuracy in modelling the thermal balance with a correlation coefficient equal to 0.997, 0.998, 0.996, and 0.992 for useful work, heat loss through exhaust, heat loss to the cooling water, and unaccounted losses, respectively.

The overall result shown in the literature indicate that using artificial intelligence techniques is a promising method to utilize in engine performance prediction instead of using time consuming and high cost experimental works or performing complex numerical calculations for performance studies

III. MOTIVATION

With the advancement of engineering technologies in alternate energy generation, thrust has been directed towards developments of the Stirling engines. The main objectives for the development of clean engines have been to firstly minimize the pollutants exuded, minimizing costs associated with manufacturing and improving the quality of finished products. Attempts have been made by researchers towards defining, understanding and developing remedial measures to improve the performance of the Stirling engines. Significant research in reducing the escaping working fluid during the engines operations, improving the period to speed and power changing requirement and etc. have been carried out. The engines requirements differ in terms of suitable features depending on how the engines elements or parameters are employed inside a Stirling engine [10]. This motivates the use of an alternative method to accurately predict parameters for the Stirling engine to avoid using performing experimental works or performing complex numerical calculations. The use of artificial neural networks (ANN) trained by particle swarm optimization (PSO) and ANFIS methods in predicting the engines non-linear properties are proposed. The pressure and the engine speed value were identified as the most important parameters affecting the power and torque of the engines. Through this, the relationship between the engine speed, the pressure, power and torque is reported.

IV. PROPOSED METHOD

In this work, the prediction performance of the ANN, ANFIS and ANN model trained by PSO have been investigated. MATLAB user interface tools and command line functionality has been used to facilitate the development of the models. To use the network, one needs to accumulate an adequate amount of data samples which will be divided into two sets. The first sample of data is used to train the network. This set of data is populated into Matlab with the solution provided, while the second set of data is populated into Matlab without a solution to validate the prediction accuracy of the trained network. The networks structure shown in Figure 2 and 3 represents the engine speed and the mean pressure as inputs; and the power and torque as the output of the networks. The torque and power estimations were computed separately. The engine speed and torque values where entered into the software to obtain the torque first, then entered for the second time into MATLAB to compute for the power values. Experimental data from work done by Karabulut et al. is used to train and assess the two algorithms [1]. Table 1 represents the data samples used in the study to test the performance of the ANN model, the ANN model trained with PSO and the ANFIS model. 48 data samples are used in the study. The data is divided into two sets: training and testing data sets. The first 38 data samples were used for training the network. This set of data is populated into Matlab with the solution provided. The remaining 10 data samples, which were not included in the training process, are used to verify the prediction capability of the network models. The data sample consists of values of pressure ranging from 1 bar - 4 bars and engine speed values ranging from 280rpm - 750rpm.

Table 1: Values used for heat transfer coefficient

Experiment No.	**Pressure (Bar)**	**Engine Speed (rpm)**	**Power (W)**	**Torque (Nm)**
1	1	350	42	1.124
2	2	350	62	1.62
3	3	350	70	2
4	4	350	75	1.95
5	1	375	45	1.12
6	2	375	64	1.58
7	3	375	82	2.06
8	4	375	79	1.9
9	1	400	48	1.115
10	2	400	65	1.47
11	3	400	92	2.12
12	4	400	83	1.875
13	1	425	49	1.06
14	2	425	65.5	1.375
15	3	425	102	2.12
16	4	425	85	1.8
17	1	450	50	1
18	2	450	44.5	1.28
19	3	450	108	2.1
20	4	450	88	1.78
21	1	475	48.5	0.925

22	2	475	63.5	1.22
23	3	475	111	2.08
24	4	475	89	1.68
25	1	500	47	0.865
26	2	500	61.5	1.1
27	3	500	114	2.04
28	4	500	87	1.59
29	1	525	45	0.8
30	2	525	59	1.06
31	3	525	115	2
32	4	525	85	1.51
33	1	550	42	0.75
34	2	550	55	0.875
35	3	550	114	1.8
36	4	550	81	1.3
37	1	575	37	0.65
38	2	575	49.5	0.79
39	3	575	111	1.77
40	4	575	77	1.22
41	1	600	30	0.425
42	2	600	45	0.625
43	3	600	108	1.75
44	4	600	79	1.09
45	1	625	23	0.4
46	2	625	38	0.5
47	3	625	101	1.5
48	4	625	62	0.89

V. CRITERIA FOR PERFORMANCE MEASUREMENT

The multiple correlation coefficients have been used to assess the AI models performance for the prediction. These coefficients are obtained using the following equation [10]:

$$R^2 = 1 - \frac{\text{Fitness}}{\sum(\text{Recorded value} - \text{Mean Recorded value})}$$

With the fitness given by:

$$\text{Fitness} = \sum(\text{Recorded value} - \text{Network predicted value})$$

The R^2 calculates the fit between the predicted values and the original experimental data. The closer the multiple correlations are to one, the more accurate the network is.

The Root Mean Square Error (RMSE) has been used to measure the data dispersion around zero deviation. It has been obtained as follows:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum(\text{network predicted value} - \text{recorded value})^2}$$

Where N represents the number of data.

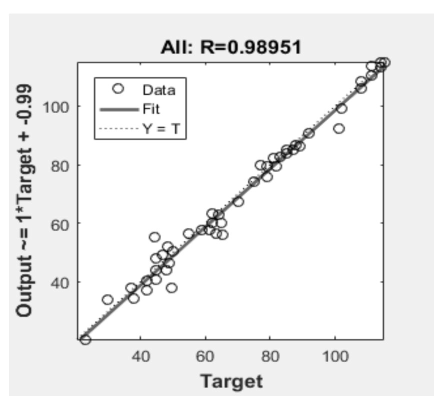
The smaller the value of RMSE is, the more accurate the predicted values are. The computational time that was taken for the models to be trained and provide prediction is measured and used as an additional performance assessment criterion.

VI. RESULTS AND DISCUSSION

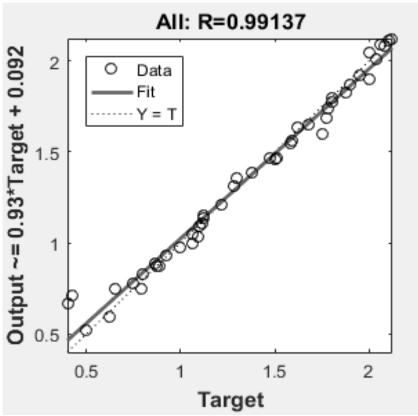
The relation of engine speed, pressure, power and torque is illustrated in the figures 4-6 below. Table 1 reveals that the ANFIS model has the highest R^2 and lowest RMSE values for both the power and torque prediction values. The R^2 and RMSE values for the ANN-PSO algorithm indicate that the model requires further development as the R^2 values are significantly lower than those of the ANN and ANFIS models. Figure 4 (a) and (b), Figure 5 (a) and (b), Figure 6 (a) and (b) show the regression plots presenting the R^2 values obtained with ANN, ANN trained by PSO and ANFIS for the power and torque respectively. Figure 7 (a) and (b) shows how the ANN PSO and ANFIS models compare to the experimental data. The graphs re-iterates what Table 1 is depicting as the ANFIS model appears to be match the experimental values better then the ANN and ANN-PSO models. The time taken for the ANFIS and ANN trained by PSO models to compute was 3.15 seconds and 129.94 seconds respectively. This finding implies that the performance of power and torque could be predicted using the ANFIS model with higher accuracy.

Table 2: ANN, ANN-PSO and ANFIS performance results

	Power		**Torque**	
	R^2	**RMSE**	**R^2**	**RMSE**
ANN	0.989	3.869	0.991	0.138
ANN-PSO	0.960	14.43	0.917	0.47
ANFIS	0.99	2.56	0.996	0.138

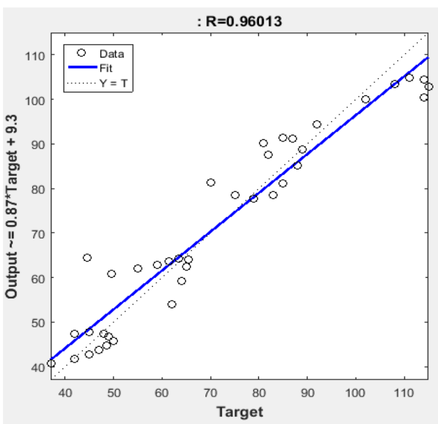


(a)



(b)

Fig.4. (a) ANN regression plots for training, testing and validation for power prediction (b) ANN regression plots for training, testing and validation for torque prediction



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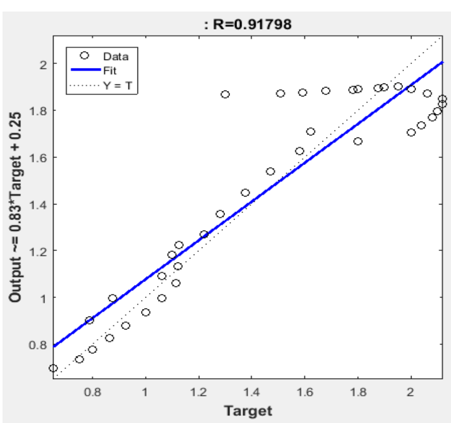
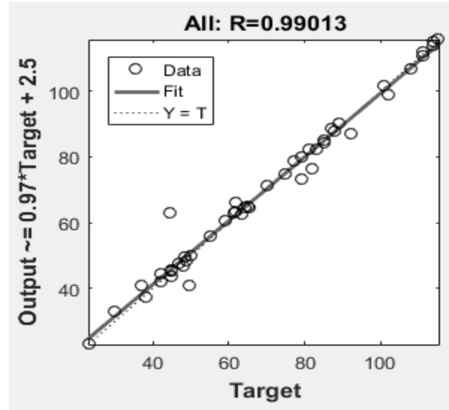
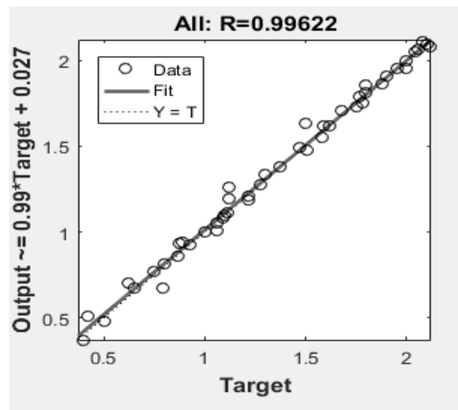


(b)

Fig.5. (a) ANN-PSO regression plots for training, testing and validation for power prediction (b) ANN-PSO regression plots for training, testing and validation for torque prediction

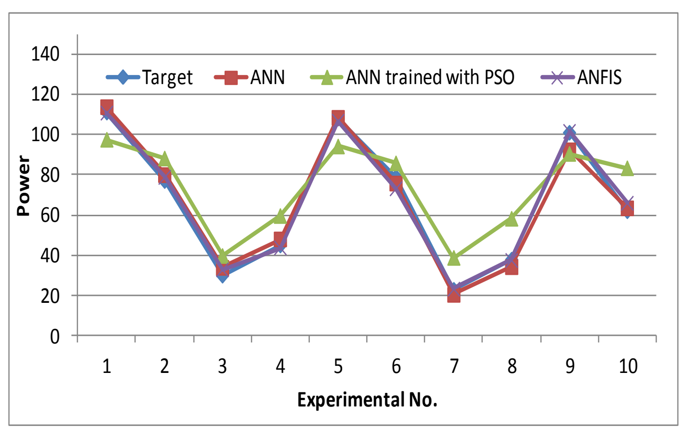


(a)

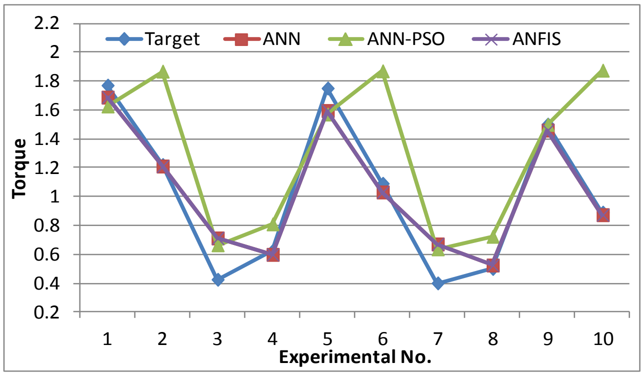


(b)

Fig.6. (a) ANFIS regression plots for training, testing and validation for power prediction (b) ANFIS regression plots for training, testing and validation for torque prediction



(a)



(b)

Fig.7. (a) ANN, ANN-PSO and ANFIS predictions vs. target value power value (b) ANN, ANN-PSO and ANFIS predictions vs. target value torque value

VII. CONCLUSIONS

In this study, three general approaches are taken into consideration to predict the power and torque of a Stirling heat engine. Modelling methods of a simple ANN, ANN algorithm trained by PSO and ANFIS are utilised to estimate the two parameters. The ANN model trained by PSO is referenced from the unpublished paper developed by Alam [5] while the ANN and ANFIS model are developed for the study. MATLAB is used to implement and develop the models. The R^2 value, the Root Mean Square Error and the computational time are used to measure the performance of the proposed approaches.

The evaluation of the results indicated that the ANFIS was able to predict with good accuracy the torque and power of the Stirling engine performance over a range for different operational conditions while the ANN and ANN trained by PSO showed inferior performance in accurately predicting the power and the torque of a Stirling engine

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