

## **PREDICTION OF INTERNAL COMBUSTION ENGINE PERFORMANCE USING ARTIFICIAL INTELLIGENCE**

### **PREDIKSI PERFORMA MESIN MOTOR BAKAR MENGGUNAKAN KECERDASAN BUATAN**

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#### **Abstract**

The potential of artificial intelligence (AI) application for prediction of internal combustion engine performance is assessed in this paper. A literature survey on this subject is first reviewed, in which previous researches utilized the advance of artificial neural networks (ANN) as one type of AI. Previous works commonly obtained the data from experimental engine tests. Under the same engines, they varied the fuel compositions or the engine operating conditions. Whereas in this study, an ANN model is developed to calculate the inputs from an engine simulation software package database and to predict the engine performance based on the simulation software outputs as the ANN target outputs. Results from the ANN model in the "learning" step indicates good agreement with the software simulation outputs. Improvement and development of the program are required, including optimization of the ANN model architecture, such as the choice of activation function, the number of neurons in the hidden layer, and the number of iterations, as well as the number and option of input engine parameters. The ANN model seems promising to predict engine performance, with root mean square errors in the range of 0.4-1.8%.

Keywords: Artificial Intelligence; Neural Networks; Engine Performance.

#### **Abstrak**

*Kecerdasan buatan (artificial intelligence - AI) telah dikenal sebagai cara pendekatan baru untuk menggantikan metode pengujian yang memerlukan biaya tinggi dan waktu lama; bahkan juga sebagai alternatif dari simulasi numerik yang memerlukan algoritma yang rumit. Potensi aplikasi AI untuk memprediksi performa mesin motor bakar dibahas dalam makalah ini. Para periset AI sebelumnya menggunakan data hasil pengujian engine sebagai data input dan data target untuk pembelajaran program jaringan syaraf buatan (artificial neural network - ANN) sebagai salah satu bentuk AI, dengan memvariasikan komposisi bahan bakar dan parameter operasional mesin. Namun pada makalah ini, dilaporkan pengembangan suatu model ANN dimana inputnya diperoleh dari database geometri dan parameter operasional mesin dari suatu software simulasi performa mesin motor bakar, sedangkan outputnya dihitung berdasarkan output software simulasi tersebut sebagai target. Hasil menggunakan model ANN mengindikasikan bahwa ANN dapat memprediksi secara baik performa mesin meski pada tahap pembelajaran perlu dilakukan uji coba, optimasi setting parameter model ANN. Setting yang perlu dioptimasi adalah jenis fungsi aktivasi, jumlah neuron pada hidden layer, dan jumlah iterasi, disamping juga jumlah dan jenis input parameter mesin. Metoda ANN ini cukup menjanjikan untuk dapat memprediksi kurva performa mesin, dengan root mean square error pada kisaran 0,4-1,8%.*

*Kata kunci : Kecerdasan Buatan; Jaringan Syaraf; Performa Mesin.*

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## INTRODUCTION

Models of transportation problems often contain complex and non-linear relations between variables describing their dynamic behavior. The application of artificial intelligence (AI) methods, which combine elements of self-learning, adaptation, and self-organization, enables the effective elaboration of such models. Artificial neural network (ANN) is one type of AI that models the behavior of biological (neuron) brain. It is the dominant representative of processing algorithms related to artificial intelligence. The application of ANN for the transportation sector, especially automotive engines, has been reviewed in literatures <sup>1-7</sup>.

Artificial neural networks were proposed in the 1960s and introduced into transportation research in the 1990s. Various areas of ANN applications have been studied, e.g., evaluation of driver behavior, determination of road traffic parameters, evaluation of road surface, detection and classification of vehicles, traffic pattern analysis, and incident detection, freight operations, traffic forecasting, road traffic control, and transport policy and economics. In recent years, this method has been applied to various disciplines, including automotive engineering, in the forecasting of engine thermal characteristics under different working conditions. The prediction by a well-trained ANN is much faster the conventional simulation programs or mathematical model as no lengthy iterative calculations are needed to solve differential equations using numerical methods.

Simulation and modelings are performed in order to reduce the time and cost as in the case of experimental investigations. Therefore, alternative ways are developed by predicting the performance (and emissions) using an ANN with a fewer number of experimental studies. Previous research has shown that the ANN model can predict and forecast engine performance and emissions with minimal error.

Many research projects have been conducted in this subject, for example, to examine performance and emissions from biodiesel <sup>2</sup>). Researchers are interested in knowing the performance of diesel engines for various operational conditions. A new modeling technique using ANN can be applied to estimate the desired output parameters when enough experimental data is provided. It has been used for prediction of diesel emissions using a cylinder combustion pressure <sup>3</sup>), for modeling of

valve timing in an SI engine <sup>4</sup>), for predicting diesel lubricity <sup>5</sup>), and many other aspects.

For engine applications, the number of neurons for the hidden layer, as well as the number of samples for training, validating, and testing purposes, plays an important role in the building of ANN architecture <sup>6</sup>). Previous studies have shown various data for training, validating, and testing for engine emissions and performance prediction <sup>1-3</sup>). Those studies have revealed that the best training algorithm for engine emissions predictions are back-propagation neural networks with Levenberg–Marquardt <sup>7</sup>). The scope of previous works above is summarized in Table 1.

Table 1.  
ANN in engine research by previous researchers

Reference	[Arumugam et al., 2012] <sup>2</sup> )	[Traver et al., 1999] <sup>3</sup> )	[Najafi et al., 2009] <sup>7</sup> )
<b>Inputs</b>	% blend, P, BSFC, T <sub>exh</sub>	Peak pressure, ignition delay, heat release, ...	% blend, engine speed
<b>Number of input</b>	4	7	2
<b>Number of Hidden Layer</b>	2	3	1 (20 neurons)
<b>Output</b>	Thermal efficiency, NOx, CO2	HC, NOx, CO, CO2	HC, NOx, CO, CO2, thermal efficiency, BSFC, power
<b>Number of output</b>	3	4	9
<b>Number of data sets</b>	105	64	
<b>RMSE</b>	0.02	n.a.	0.49
<b>Activation function</b>	n.a.	tanh	Sigmoid and tanh
<b>R<sup>2</sup></b>	0.948	0.95	0.99
<b>Type of propagation</b>	backward	backward	Backward
<b>Training Algorithm</b>		Levenberg-Marquardt	
<b>Software</b>	n.a.	Neuro-Shell	MATLAB

More recent works have shown the ability of prediction of engine performance and emission using ANN models <sup>8, 9, 10, 11, 12, 13, 14, 15</sup>)

In this paper, a methodology for predicting the engine performance is developed using an ANN model, and comparing the results with an engine simulation package “Engine Analyzer Pro,” as described below.

The Engine Analyzer Pro (EAP) is a comprehensive software package for the professional engine builder or engineer to simulate an engine build-up or modification <sup>16)</sup>. It has the ability to input various combinations of cams, heads, intakes, superchargers, etc. and to see the effect on torque, power, airflow, fuel flow, maximum cylinder pressure, volumetric efficiency, etc. It has a set of built-in database engine libraries of various engine types, ranging from 1 to 12 cylinders, from old to recent productions, both gasoline and diesel engines. The user has the flexibility to input his/ her data, retrieve existing data from the library, or to modify them from the library.

The EAP software provides an engineering estimate of what should occur when general modifications are made based on internal combustion engine theory and general physics and thermodynamics. It cannot predict exact torque and power curves but is still a vital tool for engine development. Therefore, the use of the software results is as a guide of how an engine should perform under near optimum conditions.

The EAP was validated using dynamometer data from many different engines, from small to big engines within the range of 5-500 HP. In general, the EAP's torque and power results compared within 7% of the actual dynamometer data at most engine speeds. The agreement is best near the torque and power peaks <sup>16)</sup>.

## THEORY

ANN is a non-linear computer algorithm and can model the behavior of complicated non-linear processes. It does not need an explicit formulation of physical relationships for the concerned problem.

Neural networks are composed of simple elements which are operating in parallel. These elements mimics the biological nervous system of the human being. Initially in the “training” stage, the neural network can be programmed to perform a particular function by adjusting the weights between the adjacent elements. The basic processing element of a neural network is a neuron, as depicted by Fig. 1.

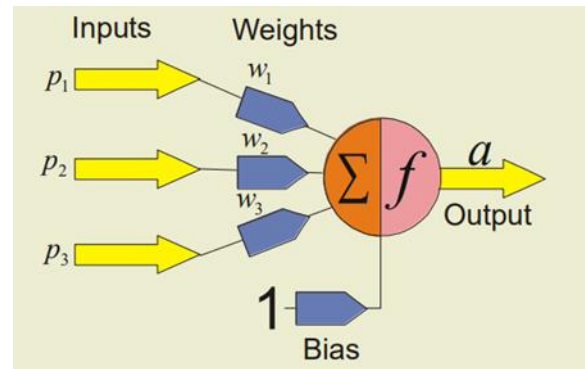


Figure 1.

Schematic representation of a neural network

A neuron first forms the sum of weighted inputs  $p$ , and after adding the bias  $b$ , an activation function  $f$  is operated, yields an output  $a$ , given by <sup>17)</sup>:

$$a = f(\sum p_i W_i + b) \quad (\text{Eqn. 1})$$

where  $W_i$  is the interconnection weight of the input vector  $p_i$ , and  $b$  is the bias for the neurons. The activation function may use “sigmoid” form as defined by:

$$\varphi(z) = \frac{1}{1+e^{-z}} \quad (\text{Eqn. 2})$$

or may be in the form of “hyperbolic tangent” (often abbreviated as “tanh”) function:

$$\varphi(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}} \quad (\text{Eqn. 3})$$

Both activation functions above were tested in this study to check which one is more suitable. The method of modifying the weight in the connections between network layers with the objective of achieving the expected output is called “training” a network.

Neural networks operate like a “black box” model, in which the user does not need to know any detailed information about the system. On the other hand, they have the ability to learn the relationship between input and output. The network usually consists of one input layer, one or several hidden layers, and one output layer, as shown by Fig. 2.

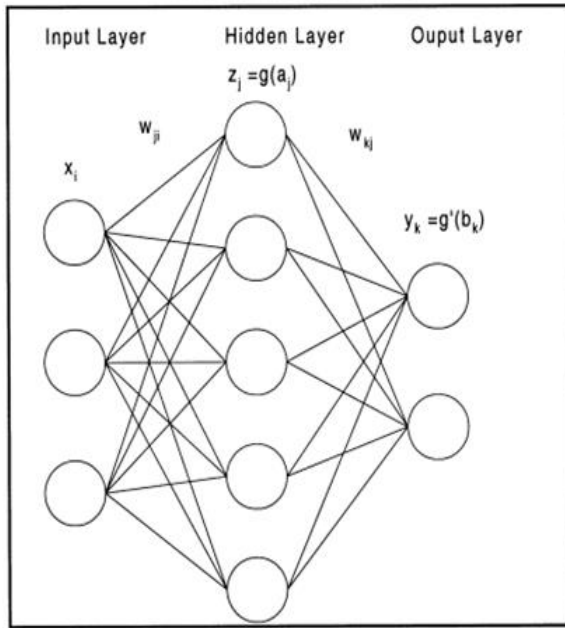


Figure 2. Typical three layers of neural network architecture

Various algorithms are used for training the network, one of which is online back-propagation. The performance of the network outputs is evaluated by regression analysis between the network outputs and the actual outputs. The criteria used for measuring network performance are the correlation coefficients. The error identified during the learning steps may use the root-mean-squared-error (RMSE) method, which is defined as :

$$RMSE = \left( \frac{1}{p} \sum_j |t_j - o_j|^2 \right)^{1/2} \quad \text{(Eqn. 4)}$$

Where  $t$  is the target,  $o$  is the output, and  $p$  is the number of the neurons <sup>7)</sup>.

**METHODOLOGY**

The methodology used here to assess the potential of the ANN model for predicting the engine performance is by first running the engine simulation EAP under various engine sets and record the performance outputs. Engine input parameters from the simulation package database library are taken as the input of the ANN model. Most of the built-in data from the library were already validated by dyno tests, and hence it is expected that the simulation results sufficiently represent the real engine performance.

Then the output is used to train the ANN model; in other words, the output of the engine simulation software EAP is used for the target output of the ANN model. The model is self-developed by the authors, using the MATLAB software version R-2014a <sup>18)</sup>.

Unlike previous researchers that run different combinations of fuel but using the same (one) engine, here several different engines by simulations are executed. For the first trial, only engines with the same number of cylinders, in this case, eight cylinders, are selected from the EAP database library.

For the training step, a number of 12 engine sets were exercised, as listed in Table 2. The 12 engines represent those of lower speed engines (engine A-D), medium-speed engines (engine E-H), and higher speed engines (engine I-L). Those engine classes have peak torques occur at about 3500, 4500, and 5500 rpms, respectively.

Table 2. Engine Types (8 cylinders) for training the ANN model

Engine Code	Engine Name	Engine capacity (litre)	Rated Power (HP)	Remarks
A	302-4V	4.942	210	Low-speed engines
B	87- 302-E.VI	4.942	233	
C	351W-GT4.0	5.766	249	
D	1969 Ford 428 Cobra	6.989	335	
E	RSTR-SBC.HEV	5.819	300	Medium-speed engines
F	LATE-MODEL	5.819	372	
G	1969 Pontiac GTO 400	6.554	366	
H	STREET-420	6.889	525	
I	98-WNSTN.CUP	5.782	720	Higher speed engines
J	INJ-SBCH.EV	6.666	692	
K	500-FORD	8.186	700	
L	434-SBCH.EV	7.111	675	

The engine input parameters are listed in Table 3, which include engine geometry parameters (bore, stroke, connecting rod length, compression ratio), aspiration (intake and exhaust valves diameters, and airflow), and valve timings.

Engine speed (rpm) becomes another input parameter, which is varied from the minimum to maximum speed within the specified range. The engine speeds are picked up from 2000 rpm to 6000 rpm with an interval of 500 rpm.

Table 3.  
Engine Input parameters

Parameters	Unit	Engine Code											
		A	B	C	D	E	F	G	H	I	J	K	L
Bore	mm	101.6	101.6	101.6	104.9	102.36	102.36	104.65	105.54	104.78	105.54	111.51	105.54
Stroke	mm	76.2	76.2	88.9	101.09	88.39	88.39	95.25	98.43	83.82	95.25	104.78	101.6
Rod length	mm	129.29	129.29	139.7	164.82	152.4	152.4	168.28	148.59	152.4	152.4	166.12	152.4
Compression ratio	--	8.4	9	8.5	10.5	10	10	10.75	11	12	14.5	10	11.2
intake valve diameter	mm	45.21	45.21	45.72	53.09	51.31	51.31	53.59	51.31	54.61	53.98	52.91	55.88
exh valve dia	mm	36.83	36.83	38.1	41.91	40.64	40.64	44.96	40.64	41.15	41.28	42.06	41.91
Gas flow	ft3/min	600	540	680	700	290	370	750	1000	950	4595	1120	850
Intake cam centerline	deg	114.5	114.5	115	119	99.5	106	110	106	104	99	110	110
Exh valve centerline	deg	114	114	111	118	113	106	110	114	108	113	110	110
Intake valve duration	deg	211	211	190	193	247	254	232	236	268	260	276	252
Exh valve duration	deg	206	206	204	206	256	262	238	244	272	268	286	258

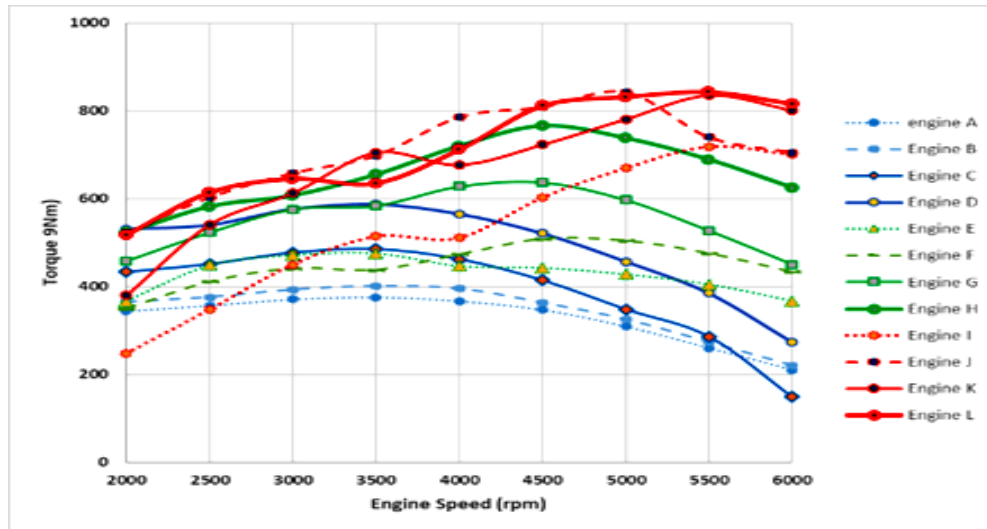
The engine performance (output parameters) to observe are the Torque, Power, brake specific fuel consumption (BSFC), brake means effective pressure (BMEP), thermal efficiency, and volumetric efficiency. Several ANN model architectures are tested in terms of activation function, the number of iterations, and the number of neurons in the hidden layer.

## RESULTS AND DISCUSSIONS

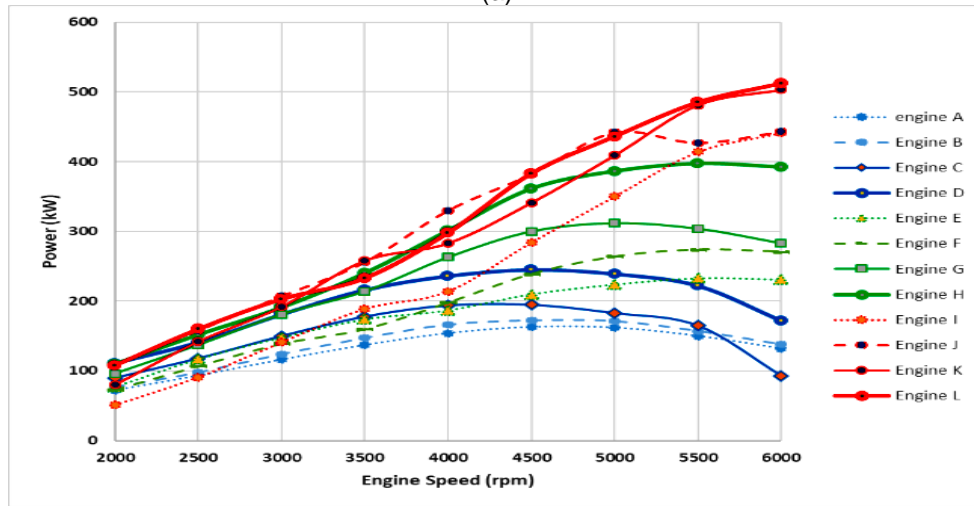
Calculated Torque, power, and BMEP as a function of engine speed resulted from the

EAP simulation software are shown by Fig. 3 (a-c)- Calculation time for each engine set takes about 5-6 minutes. Results for BSFC, thermal efficiency, and volumetric efficiency curves are also obtained, but not shown here.

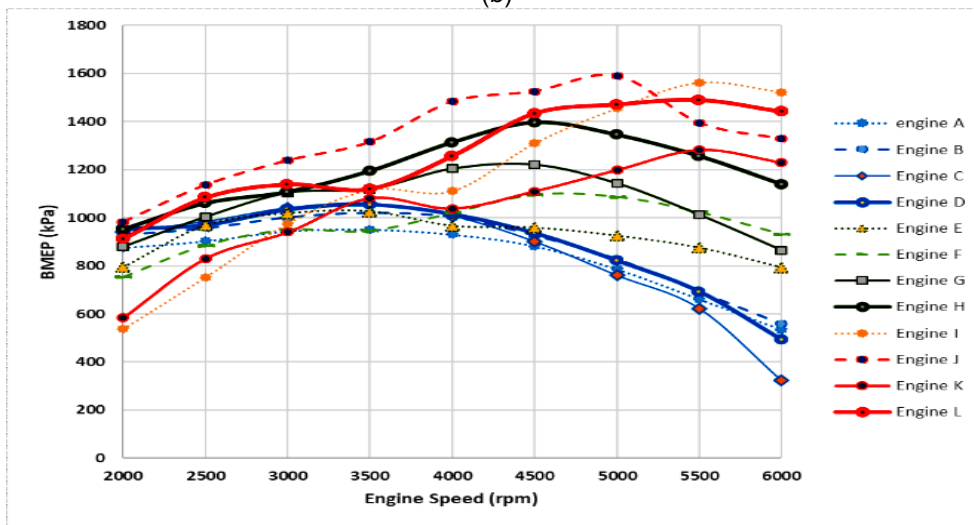
From the shapes and size of performance curves in Fig. 3, it can be seen that the 12 selected engines represent various characteristics of engines, from "traction" engine (i.e., high torque low speed) to "racing" engine (i.e., high power high speed), and those of in between.



(a)



(b)



(c)

Figure 3.

(a) Torque, (b) Power, and (c) BMEP curves as obtained by the EAP software

After obtaining the engine performance output from EAP software, the same input and output parameters of the EAP software are then used to train the ANN model; i.e., the output of the EAP is used for the target output of the ANN model. Both activation functions, i.e., sigmoid and hyperbolic tangent functions, are tested consecutively. The number of iterations is set to 100000, and the number of neurons in the hidden layer is set to 40.

The ANN model result for all engine performance parameters is obtained, but for the sake of brevity, only torques are shown in Fig. 4. It can be seen that whereas the sigmoid activation function (shown as dashed black curve/ line) agrees partially for several engines. The result for hyperbolic tangent function (shown as red square markers) fits very well with the target (shown as solid blue lines with blank square markers) overall engines.

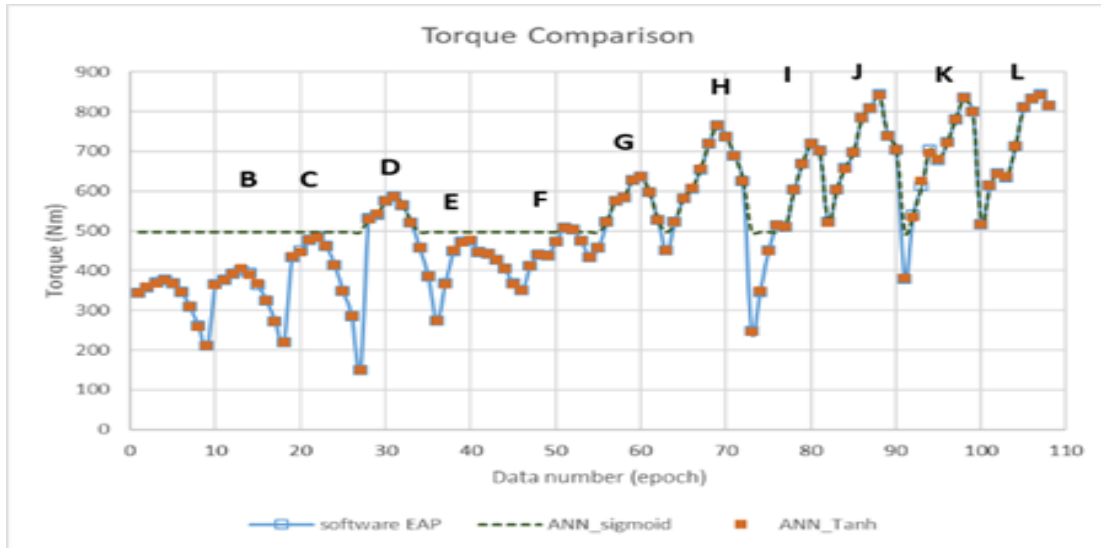


Figure 4.  
 Comparison of Engine Torque calculation using different activation functions

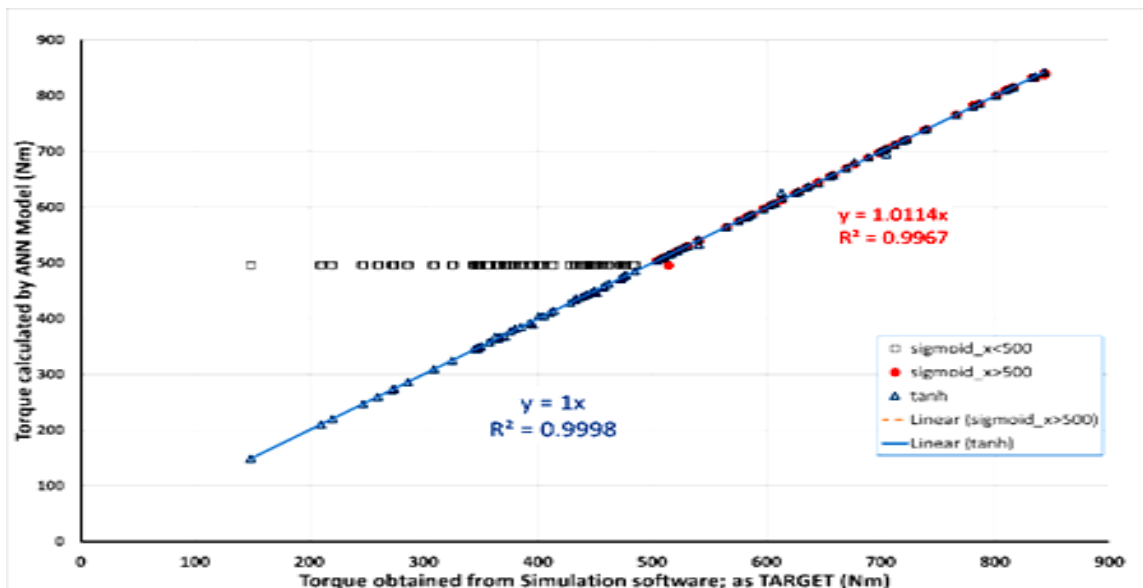


Figure 5.  
 Correlation between the Torques as calculated ANN model output vs. the target output,

using sigmoid activation and tanh activation function.

The RMSE values, as calculated using Eqn (3) for each condition, are shown in Table 4. It can be seen that the error of the ANN model using the hyperbolic tangent activation function is much lower than that of the sigmoid function.

Table 4.  
The effect of activation function on RMSE.

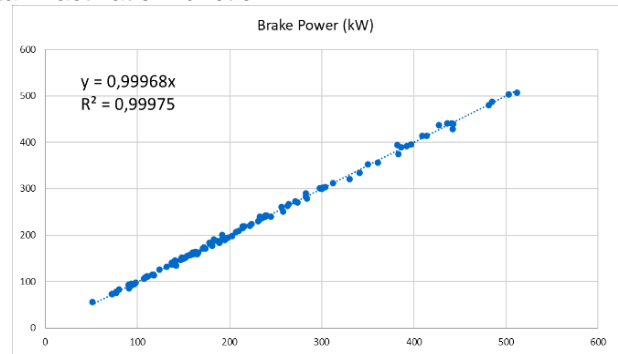
	Activation Function	# of iteration	# of neuron	# of engine	RMSE
1	sigmoid	100000	40	12	95.26
2	tanh	100000	40	12	2.11

The drawback of the sigmoid activation function, in this case, is also obvious from Fig. 5, which shows the correlation between the target output (in this case is torque obtained from engine simulation software) against the ANN calculated output.

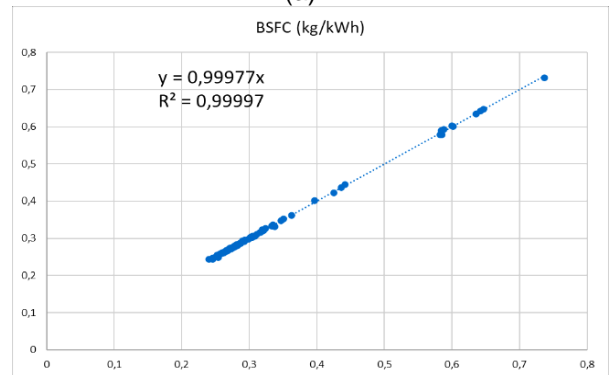
As shown in Fig. 5, the model using the sigmoid activation is good in the upper half of the data range (shown by red solid circle markers), but it remains constant at a value of 495 for target values of less than or equal to 495 (shown by black square markers). If these data are ignored or removed, correlation of the ANN output to target value fits (shown by the dashed red lines) sufficiently well with the degree of correlation fit as measured by the R-squared value of  $R^2 = 0.9967$ . Much better improvement using the hyperbolic tangent function is obvious from Fig. 5 (shown by the triangle markers) and linear regression of  $R^2 = 0.9998$  (shown by the solid blue lines).

From here on, only the results using hyperbolic tangent functions are shown and discussed. Correlation between the other target outputs, i.e., power, BSFC, BMEP, thermal efficiency, and volumetric efficiency, as obtained from engine simulation software against the ANN calculated output are shown in Fig. 6 (a-e) subsequently.

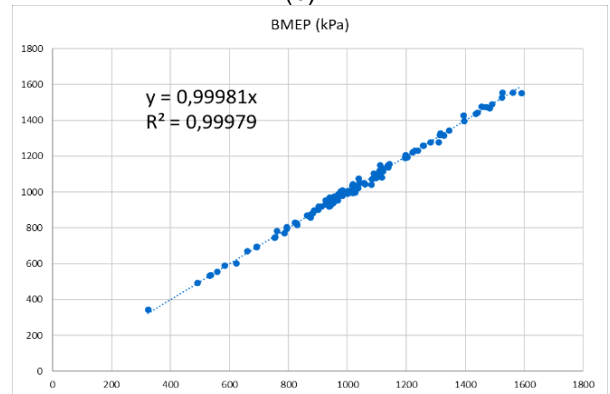
All the linear trend lines of the outputs fit very well, as indicated by high R-squared values of very close to 1, as shown in the graphs and also summarised in Table 5.



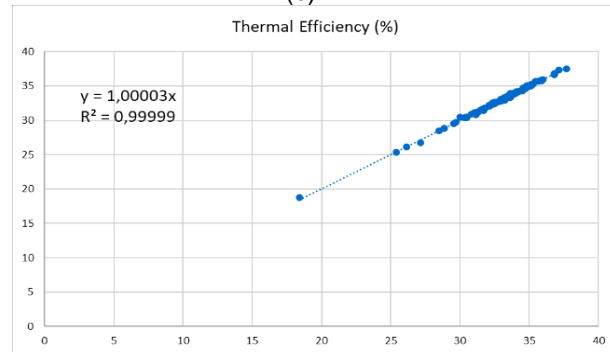
(a)



(b)

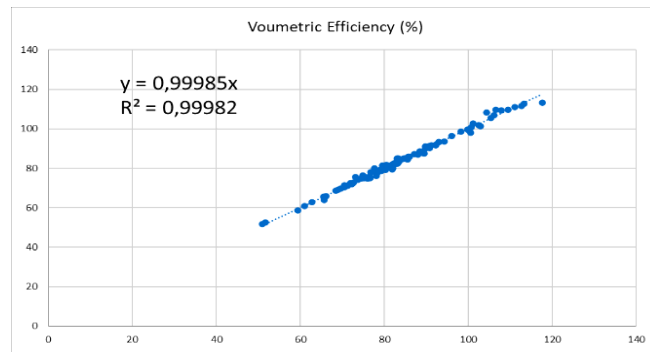


(c)



(d)





(e)

Figure 6.

Correlation between the calculated ANN model output vs. the target output, using tanh activation for (a) Power, (b) BSFC, (c) BMEP, (d) thermal efficiency, and (e) volumetric efficiency

Table 5 also shows the range of RMSE and percentage errors, which are in the range of 0.4-1.8. Considering the accuracy of engine dyno tests, which typically 2-5%, the results of the ANN model here are regarded as acceptable.

Table 5.

List of RMSE and  $R^2$  obtained using ANN Model (tanh function)

Parameter	Average	RMSE	% error	$R^2$
1 Torque (Nm)	522	2.11	0.40	0.99999
2 Power (kW)	222	3.89	1.75	0.99968
3 BSFC (kg/kWh)	0.319	0.0018	0.57	0.99997
4 BMEP (kPa)	1031	15.27	1.48	0.99979
5 Thermal effi. (%)	32.9	0.12	0.38	0.99999
6 Volumetric Eff. (%)	72.8	1.13	1.36	0.99982

Having obtained satisfied convergence and acceptable accuracy in this training step, the next step forward is that the ANN model will be tested for other engine library data to be compared with the EAP simulation software. Effect of varying the number of iterations and the number of neurons will be reported in our incoming paper.

## CONCLUSION

Based on the methodology developed in this study, it can be concluded that the application of AI, particularly in this case ANN, for predicting engine performance of various engine geometry and operations, is possible with a proper choice of ANN parameters. In the training steps, it was demonstrated that the ANN model was able to predict the performance

engine parameters. However, the choice of the activation function is most critical. In contrast, the setting of the ANN architecture, such as the number of neurons in the hidden layer, the number of iterations, the input engine parameters, etc., may be secondary factors.

Errors were found to be within 0.4-1.8%. These errors are considered acceptable for prediction of engine performance, although somewhat higher than those of typical ANN models of other cases in the literature. Difficulties arise in the selection of the engine type/ size to be picked up as data input in the training steps since performance curves output are dictated by many intertwined factors, affected not only by engine geometry but also aspiration and combustion characteristics of the engine.

Despite difficulties in determining the optimum model architecture and parameters, there was a considerable success, especially once the proper activation function is found. The method shows promise for producing performance curves, including torque, power, BMEP, etc., and thus capable of predicting performance with acceptable accuracy. It is recommended that the method should be further validated with the engine test results.

Potential applications include the development of the propulsion system of a vehicle, which includes engine selection, engine control strategies, and mutual validation of the engine modeling software with the engine test.

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## CONTRIBUTORSHIP

Lukman Shalahuddin is the main contributor, whose role is to survey the literatures, perform the review, set up methodology, analyze the results, and to supervise both the engine simulation program and the ANN program.

Adityo Suksmono is a member contributor, whose role is to provide the ANN

theoretical foundation, to write the algorithm, and to run the ANN program in MATLAB package.

Yohanes P Sembiring is another member contributor, whose role is to run the engine simulation software and to provide the data as input and output of the ANN program.

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